Abstract

Halting and reversing global forest loss is a key priority for sustainable development pathways. Multiple countries in the Global South have recently transitioned from net forest loss to net forest gain. Understanding and explaining reforestation patterns is necessary to better understand land cover dynamics and create more effective sustainability policies. We show that international migration – a key feature of globalization in the 21st century – spurs a transition to greater forest cover in Nepal. Although some aspects of globalization - agricultural commodity production and trade in particular - have been identified as contributing to deforestation, the effects of international migration are less well understood. Using data from Nepal's national census (1.36 Million households) and from high-resolution forest cover change, we find that international outmigration is associated with substantial increases in local forest cover, even after controlling for multiple confounding factors. We find that areas with international outmigration levels above the median in 2001 were 44% more likely to experience net reforestation between 2000-2012. This effect of outmigration is mediated by changes in population density and in household agricultural activity. Effects of outmigration are higher in more agriculturally suitable areas, suggesting that migration-driven forest transitions are influenced by agricultural production systems. We provide new empirical evidence of forest transition driven by international migration and a generalizable analytical approach to the study of forest transitions using secondary global and national datasets. Our results suggest that actions to reach global sustainability, biodiversity targets, and reduced emissions can be better designed and targeted by taking into account the effects of international migration on natural resources and ecosystems.

Highlights:

- Areas with higher levels of international outmigration in Nepal experience more reforestation.
- International migration effects are mediated by reductions in population density and agricultural activity.
- International migration effects on forest resurgence are constrained by agricultural production systems.
- Sustainable development initiatives should consider the effects of human migration on ecosystems.

Keywords: forest transitions | sustainable development goals | labor markets

1. Introduction

Forests are critical to sustainable development because of the extent and magnitude of their contribution to carbon sequestration, biodiversity conservation, watershed protection, and livelihood contributions among other societally valued benefits (UNFCCC, 2016; United Nations, 2015). Although deforestation continues to increase in many parts of the world, several countries in the Global South have transitioned from deforestation to reforestation during the past 15 years (Meyfroidt and Lambin, 2012; Rudel et al., 2005; Sloan and Sayer, 2015). Scholars have devoted substantial attention to elucidating the drivers of deforestation, yet the processes driving improvements in forest cover need to be better understood, particularly in the Global South.

The increased movement of labor is a key facet of globalization that may affect natural resource use and requires more careful empirical study (de Haas, 2012; Kull et al., 2007). Global human migration flows alter local, regional and national socioeconomic processes through remittances, and changes in labor markets and population structures. In 2010, approximately 170 million international migrants contributed an estimated $432 billion to the global economy (de Haas, 2012), with the vast majority of labor flows originating from countries in the Global South (Abel and Sander, 2014; IOM, 2014). Understanding the influence of these flows on natural resources and the environment is critical to design better strategies for natural resource protection.

Migration flows and remittances are considered key drivers of forest transitions and their effects on reforestation are thought to be driven by a series of overlapping mechanisms (Hecht et al., 2015; Hecht and Saatchi, 2007; Kull et al., 2007). Three key mechanisms that have been proposed to explain reforestation as a result of migration include: (i) remittances that are invested in financing the migration of entire households (Acharya and Leon-Gonzalez, 2016), leading to forest resurgence on abandoned agricultural areas (Aide et al., 2000); (ii) remittances that reduce recipient households' levels of poverty and dependence on agricultural production and/or forest products such as firewood or building materials (Manning and Taylor, 2014; Robson and Berkes, 2011); and (iii) reductions in the amount of agricultural labor available at the household level, leading to a reduction of agricultural production and a resurgence of forests on marginal lands (Manning and Taylor, 2014; Schmook and Radel, 2008).

However, the relationship between migration, labor shortages and agricultural production also appears to be highly context dependent (B. Davis et al., 2009). For example, outmigration may not change forest cover if migration is only seasonal and household members return to provide labor at key times or if remittances are used to replace lost labor through non-labor inputs (e.g., fertilizers, pesticides and herbicides, or small-scale mechanization) or by hiring in additional workers. Critically, outmigration can also lead to forest loss and increase agricultural activity if remittances are invested in more extensive agricultural production (e.g., through additional cattle ranching observed in several Latin American contexts) (Alix-Garcia et al., 2013; Davis and Lopez-Carr, 2014; Taylor et al., 2016; VanWey et al., 2012).

Our study tests for an overall relationship between international outmigration and forest cover, and for mechanisms that can explain the positive relationship we observe. Our results support theories that the magnitude of the effect of migration on reforestation depends on the type of migration and the type of agricultural production system. International migrants tend to send back higher remittances than national migrants and are often away for longer periods of time (VanWey et al., 2012), making it uneconomical for them to remain involved in household agricultural activities. If households reduce agricultural activities without changing production systems, it is thus a logical progression that international migration will lead to reforestation because less land is being used. At the same time, remittances may lead to changes in production systems, and in this case agricultural land suitability matters. Theory suggests that when land inputs are limited but of high quality, remittances are more likely to be invested in agricultural intensification through additional non-labor inputs (Angelsen, 2010). This process can lead to a potential contraction of agricultural production, even in the presence of high remittances, resulting in forest resurgence on abandoned lands and more intensive, non-labor input driven production on remaining agriculturally active lands. In contrast, when additional inputs or mechanization are more difficult to implement, labor losses would be more likely accommodated by a combination of additional inputs and additional land, or shifts in the time allocation of remaining household members to agricultural production; leading to less reforestation overall.

In Nepal, a key feature of agricultural suitability is slope: steeper slopes are difficult to intensify through capital inputs, while the flatter areas, which are limited in extent, tend to be more agriculturally productive, better connected to markets, and more amenable to the use of modern agricultural equipment and non-labor inputs (Marquardt et al., 2016). Nepal, therefore, provides an interesting case in which to test the hypothesis that high international migration combined with highly agricultural suitable lands that cannot be easily expanded or transformed into less intensive systems is likely to lead to forest regeneration.

Despite the magnitude and scale of international migration as a global phenomenon, its effects on ecosystem health and forest recovery remain a matter of discussion (Hecht et al., 2015). This is because most existing forest transition studies have either focused on small-n case studies to describe how outmigration and remittances influence land-use decisions in regions of origin, or have not measured outcomes in comparison to counterfactuals. Although small-n studies have identified the conditions under which migration can lead to forest regeneration, they have paid less attention to rigorously quantifying the impact of outmigration and related pathways on improvements in forest cover, especially at larger regional or national scales (Bhagwat et al., 2014; Le et al., 2014). Although larger-n studies to date provide important information about relationships between factors (Hecht and Saatchi, 2007; Redo et al., 2012), they have not been able to account for many confounding elements of socioeconomic and environmental heterogeneity, including national level conservation and development initiatives (e.g. decentralized natural resource management policies) that might themselves act as forest transition pathways (Meyfroidt and Lambin, 2012; Nagendra, 2007).

Here, we move beyond small-n case studies by estimating the magnitude of the effect of international outmigration on forests in Nepal. To do so, we construct a comprehensive and unique national-level dataset that includes longitudinal data at the sub-district level (2001, 2011) and high-resolution forest cover change data (2000-2012). We seek to disentangle the effects of migration from other factors by matching on and controlling for a suite of key biophysical, socioeconomic and institutional covariates. The pre-processing of data using statistical matching improves causal inference of regression analyses by ensuring that treated and comparison groups are similar with respect to key covariates that influence the relationship between treatment and outcomes (Ho et al., 2007; Stuart, 2010). To better test prior forest transition theories, we also analyze the significance of different effect mediators, including changes in population density, household poverty, and household agricultural activity, and test for heterogeneity in mediating effects of the agricultural suitability of land.

2. Methods

2.1. Country selection

Several factors make Nepal a useful setting to understand the effects of migration on forest cover. Nepal is important ecologically, with globally significant biodiversity assets (Myers et al., 2000) and substantial forest cover of 5.96 million hectares of forests or 40% of the country's surface area (Ministry of Forests and Soil Conservation, 2015). Furthermore, as is the case for many nations with remaining biodiversity, Nepal has a large rural population (83% of the total population) that relies predominantly on small-scale, labor-intensive subsistence agriculture - conducted in a variety of conditions including both irrigated flat plains, which are limited in extent but highly fertile, and steep mountain slopes where agriculture is predominantly practiced on terraces (Maharjan et al., 2013; Marquardt et al., 2016).

Levels of international outmigration in Nepal are substantial (but not exceptional across the globe) in both 2001 and 2011: 15% of households sampled in the census reporting one or more household members living abroad in 2001, a proportion that nearly doubled to 29% in 2011 (Central Bureau of Statistics, 2011; 2001). The major driver of international outmigration is the availability of higher wage opportunities for relatively low-skilled labor in other countries. This pull, predominantly from Gulf countries and Malaysia, as well as a free border agreement with India, has spurred substantial migration from rural areas (Kern and Müller-Böker, 2015). Most international migrants in Nepal are young, working-aged men that typically emigrate for several years (*Table S12*). Remittances are integral to Nepal's economy; in 2013 they accounted for approximately 25% of the country's Gross Domestic Product in the year 2013 (Ratha et al., 2016).

Given Nepal's ecological importance, large rural population and high levels of international outmigration, it is itself an important region in which to understand the effects of international migration on forest cover. Our study also potentially sheds light on reforestation and migration relationships in other countries undergoing similar processes by developing a generalizable methodology using public datasets that are legally available to the public. Thus in addition to novel results about Nepal, we illustrate an important analytical approach to the study of forest transition drivers that can and should be replicated in other countries and contexts (see also (Meyfroidt, 2015).

2.2. Data and analytical approach

We assessed the effect of international outmigration on forest cover between 2000 and 2012 using longitudinal data for 2727 of Nepal's 3973 Village Development Committees (VDCs, our unit of analysis), equivalent to municipality-level administrative units in other countries[1]. We excluded 1246 VDCs because of missing or poor data, overlaps with IUCN category I and II protected areas (IUCNUNEP-WCMC, n.d.), or very low baseline forest cover. However, to ensure our results are not dependent upon the exclusion of VDCs with low baseline forest cover, we conducted an additional robustness test using the entire dataset.

We compiled our dataset from various national and global data sources (Supplementary Material), choosing the period between 2000 and 2012 because of the availability of both spatially referenced national census and high-resolution forest cover data. We used a combined matching and regression analysis to generate quasi-experimental estimates of the effect of international outmigration on forest cover. The combination of matching and regression allowed us to robustly isolate the effect of international migration on changes in forest cover by using counterfactuals and carefully controlling for multiple potential socioeconomic and environmental confounders, including baseline levels of forest cover, population density, poverty, agricultural activity, land quality. We also control for decentralized natural resource management initiatives (community forest management), which have previously been shown to be associated with the expansion of forests (Fox, 1993; Jackson et al., 1998; Southworth et al., 2012).

We also conducted a subsequent mediator analysis to estimate the effect of three non-mutually exclusive mechanisms that might mediate the effect of migration on forest cover change: 1) change in population density 2) changes in poverty, 3) changes in agricultural activity. Furthermore, we evaluated how the effect of international migration on forest cover and our mediators depends on slope, which we use as proxy measure for land agricultural suitability (Nelson and Chomitz, 2011).

[1] With the introduction of Nepal's newest constitutional reform in 2017, Village Development Committees have been dissolved and replaced by metropolitan and sub-metropolitan cities, and urban and rural municipalities.

2.2.1 International migration

We use data from the 2001 (520624 households) and 2011 (841567 households) Nepali national census (Central Bureau of Statistics, 2011; 2001) to measure the proportion of households within each year with at least one or more household members above school age (> 16 years) living abroad. We use these measures to assess median VDC-level international migration levels at baseline (2001) and 2001-2011 changes in international migration. To generate binary treatment variables for matching pre-processing, we created dichotomized variables based on national-level median estimates, classifying 2001 migration levels (baseline), or changes in these levels between 2001 and 2011, as "high" (≥ median) or "low" (< median). However, to ensure that our principal results are not dependent on the creation of binary treatment variables we also conducted a standard logistic regression using a continuous measure of migration in 2001 (Supplementary Material).

2.2.2. Forest cover change

We measured forest cover change between 2000 and 2012 relative to baseline forest cover within each VDC using the high-resolution forest cover change dataset v1.0 (Hansen et al., 2013). We measure forest change as a proportion of baseline forest cover, defined as areas with > 10% tree cover (Supplementary Material). Our measure of forest cover change clustered around zero with high kurtosis and did not meet assumptions of normality. We, therefore, converted forest cover change into a dichotomized binary variable (MacCallum et al., 2002); classifying negative change as deforestation (mean = -0.009, S.D. = 0.013) and positive or no change as reforestation (mean = 0.005, S.D. = 0.034). To ensure our results are not dependent on dichotomization, we also conducted additional robustness tests using a Lambert W (Goerg, 2015) transformed version of our forest cover change variable, as well as a set of separate analyses using continuous gross reforestation and deforestation data, and excluding 'no forest-cover change' data points (Supplementary Material).

2.2.3. Covariates and mediators

We chose a suite of biophysical (geographical area; baseline forest cover; slope and elevation; precipitation) and socioeconomic (community forestry arrangements, poverty; population density; agricultural activity; travel time to population and administrative centers; administrative areas) covariates on the basis of their potential to influence migration (selection into the treatment) and forest cover change (Supplementary Material) (Ho et al., 2007; Stuart, 2010). We focus on three non-mutually exclusive mediators that have been previously shown to be influenced by outmigration and remittances in both Nepal (Maharjan et al., 2013) and elsewhere (Southworth et al., 2012). These mediators can act as potential drivers of land-use change and forest transitions by affecting local consumption patterns and agriculture-based livelihoods (Angelsen, 2010): i) changes in population density between 2001-2011, using data from the national census; ii) changes in the prevalence of poverty between 2001-2011, measured along several dimensions including fuelwood use to control changes in forest dependence (Alkire and Santos, 2014); and iii) changes in agricultural activity between 2001-2011, measured as changes in the number of months that households dedicate to agriculture.

2.3. Matching-based regression analysis

We used matching-based regression analyses to maximize the potential to evaluate causal links between migration and forest cover changes (Ho et al., 2007; Stuart, 2010). Matching approaches differ primarily in the distance measure used to evaluate covariate balance and the number of control cases matched to each treatment case (Stuart, 2010). To ensure our results are not dependent on the choice of matching method, we use three different commonly used matching approaches: optimal full matching, propensity score matching and Mahalanobis distance matching.

We performed all our statistical analyses in *R* (R Core Team, 2016) and use the "MatchIt" package (Ho et al., 2011) for our matching analyses. We use the standardized mean difference for individual covariates as well as the propensity score for optimal full and propensity score matching to assess covariate balance before and after matching. We use a post-matching standardized mean difference of < 0.25 as an indication of acceptable balance between treatment and controls groups for individual covariates (Stuart, 2010). In all cases matching substantially increased covariate balance (Fig. A1 - A3, Tables A1 - A3). However, optimal full matching yielded a marginally better propensity score balance than propensity score matching alone (Fig. A1B and A2B), and a better balance of individual covariates than Mahalanobis distance matching (Figure A1A and A3). Because matching approaches do not provide perfectly balanced datasets, we included all covariates in subsequent regression results to control for remaining differences in the high and low migration groups. We calculated average marginal effects in STATA (SE 13). We also adjusted for spatial autocorrelation by clustering standard errors by district using the *robcov* function of the "rms" package (Harrell, 2016), and so the standard errors for our principal results are corrected for spatial autocorrelation. In all post-matching analyses the effect of migration remained positive, strong and statistically significant (Table 1), suggesting that our results do not depend on the choice of matching approach or on inflated significance due to spatial autocorrelation. Data presented in the article's main text are those obtained from optimal full matching followed by regression analysis, which we also use for all robustness checks and mediator analysis.

2.4. Mediator analysis

We defined a causal mechanism as a process whereby an intermediate variable or mediator operationalizes the effect of one variable on another (Imai et al., 2011), and focused on changes in 1) population density, 2) household poverty, and 3) household agricultural activity as potential factors mediating the effect of migration on forest cover change. Our measure of population density change was heavily right-skewed and clustered around zero with high kurtosis and was transformed using a Lambert W transformation (Goerg, 2015).

To evaluate the causal mediation effect of our three mediators, we used the "mediation" package (Tingley et al., 2014). This mediation analysis assumes that treatment assignment is independent of both outcome and mediators, and that mediators are independent from both treatment status and pretreatment confounders (Imai et al., 2011; Imai and Yamamoto, 2013). Our principal treatment variable (international migration in 2001) temporally precedes all three mediators, yet our three mediators are not necessarily mutually exclusive. To evaluate the relationship between our three mediators we ran regressions using our matched dataset, in which we sequentially model each mediator as a function of the treatment variable (international migration in 2001), all matching covariates, and the remaining two mediators. These results show that reductions in agricultural activity, poverty and population density were significantly associated with high international migration levels (Table A8). Changes in agricultural activity were also negatively related to population density changes and positively related to poverty changes. Similarly, poverty changes were positively associated with agricultural activity changes, and population density changes were negatively associated with changes in agricultural activity.

We assessed the mediating effect of changes in agricultural activity, poverty and population density using the 'mediation' package's *mediate* function, which estimates the proportion of a variable's direct effect that is attributable to a mediator, and the related *medsens* function, which performs a sensitivity analysis for the possible existence of unobserved pre-treatment covariates. Our sensitivity analysis of the main results yielded ρ = -0.1. Large values of ρ are indicative of the presence of strong confounding effects between the mediator and outcome and a potential violation of the sequential ignorability assumption. We interpret our sensitivity results as being moderately robust to the effect of confounders (Imai and Yamamoto, 2013).

Given the positive and statistically significant relationship between several of our mediators, we also use the 'mediation' package's *multimed* function, which estimates the proportion of a principal mediator's effect that is attributable to an intermediate mediator preceding it, to examine the potential role of changes in agricultural activity, poverty and population density acting as intermediate mediators of each other. To examine the mediating effects of changes in agricultural activity, poverty and population density we run several consecutive mediating analyses in which we alternate the roles of changes agricultural activity, poverty and population density as principal and intermediate mediators. Results from these analyses show that neither changes in agricultural activity, poverty or population density act as intermediate mediators of the effect of international migration on forest cover change (Table A9). In all instances, the 95% Confidence Intervals of the Average Causal Mediation Effect (ACME) overlap with zero, suggesting that their mediating effect as intermediate mediators is not significant.

To evaluate whether land agricultural suitability and labor-intensive agricultural production moderate the effect of international migration on our three mediators we included a migration and slope interaction term in our mediator analysis (Tables 2 and A8) and plot how the likelihood of changes in agricultural activity and population density (measured as predicted probabilities) changes as slope increases (Figure 4).

3. Results

We first assessed the effect of international migration on forest cover and found that among matched VDCs, those with higher levels of international outmigration in 2001 (above the median: mean probability of household outmigration = 0.251) were 44% more likely to experience net reforestation between 2000 and 2012 (logit coef. = 0.669, clustered standard errors = 0.229, P = 0.0036, Table 1, Fig. 1 and 2) than VDCs with lower levels of international outmigration (below the median: mean probability of household outmigration = 0.053).

We then evaluated the potential causal pathways through which international outmigration may influence forest recovery. We found that VDCs with higher levels of international outmigration in 2001 did experience substantial reductions in population density (coef. = -0.025 S.E. = 0.006, P < 0.0001), poverty (coef. = -0.017, S.E. = 0.004, P = 0.0001) and agricultural activity (coef. = -0.462, S.E. = 0.116, P < 0.0001, Table S9) in 2012. Reductions in population density (proportion mediated = 6.7% , P < 0.0001, Table 2, Fig. 3A) and agricultural activity (proportion mediated = 6.1%, P < 0.0001, Table 2, Fig. 3B) acted as mediators through which international outmigration increased forest cover. These results suggest that households are spending less time on agricultural activities, independent of changes in population density.

Critically, we find that the mediating effect of both changes in agricultural activity and population density appear to be moderated by slope, which we used as a proxy measure for agricultural suitability. The effect of international migration on reforestation was greatest on more agriculturally suitable lands with lower slopes (Table A8, Interaction coef. = 0.048, S.D. = 0.016, P = 0.0032). These lower sloped areas are also where we observe the largest effect of international migration on reductions in household agricultural activity (Table A8, Interaction coef. = 0.048, S.D. = 0.016, P = 0.0032) and population density (Table A8, Interaction coef. = 0.002, S.D. = 0.001, P = 0.011). The moderating effect of slope on reforestation, household agricultural activity and population density can be seen in Figure 4, which shows greater differences between high and low international migration VDCs in lower sloped areas.

4. Robustness checks and additional analyses

We conducted a series of robustness checks to validate our principal finding that international migration has been a principal driver of reforestation in Nepal (Supplementary Materials). These tests include: (i) different matching approaches and standard logistic regressions using continuous measures of migration in 2001 (full models) to ensure that our results are not dependent on our analytical approach; (ii) choice and manipulation of outcome (transformed measures of forest cover change as well as continuous measures of gross levels of reforestation and deforestation) and treatment variables (2001 - 2011 changes in migration levels) to ensure that our results are not dependent on our definitions of forest cover change or migration; and (iii) controls for internal migration levels within Nepal. In all instances, our robustness checks confirmed the effect of international migration on reforestation.

Furthermore, to confirm the effect of international migration on agricultural production, the potential mechanisms and the mediating effect of slope, we analyze a separate 3949 household panel dataset (see Supplementary Materials). We specifically test whether households with high levels of international migration (more than one migrant member) on lower slopes reduced the amount of land dedicated to agriculture and increased their use of agricultural inputs. Results suggest that high migrant households on lower slopes reduced the amount of land dedicated to agriculture (Table A13, Interaction coef. = 0.021, S.E. = 0.016, P = 0.017) and increased their use of non-labor inputs (Table A13, Interaction coef. = -0.080, S.E. = 0.035, P = 0.024) without changing the amount of hired agricultural labor (Table A13, Interaction coef. = 0.0006, S.E. = 0.030, P = 0.981). This moderating effect of slope on agricultural land and inputs can be seen in Figure A9, which shows greater differences between migrant and non-migrant households in lower sloped VDCs.

5. Discussion

Our results suggest a strong positive effect of international outmigration on forest regeneration in Nepal, particularly in more agriculturally suitable areas. We are also able to shed light on the mechanisms through which international migration affects reforestation. We demonstrate that although outmigration has significantly influenced all three potential mediators, the effect of outmigration on reforestation is mediated by reductions in agricultural activity at the household level, and larger changes in population density that are potentially driven by land abandonment as households invest remittances to relocate entire households from rural to urban areas (Acharya and Leon-Gonzalez, 2016).

Our results contribute to the general understanding of forest transitions and sustainable development policies in several important ways. First, by using a quasi-experimental approach we show that international migration can have a substantial effect on forest cover at larger regional and national scales - in our case Nepal, providing robust empirical evidence that prior case study results relating migration to increased forest cover hold at larger geographical scales.

Critically, we provide evidence that migration effects on forest resurgence are constrained by agricultural production systems. We show that contrary to what forest-transition theory would predict, migration-driven spatial reconfigurations of agricultural production do not necessarily lead to the abandonment of more marginal areas (higher sloped areas in Nepal). The patterns we observe are likely because Nepal's small-scale labor intensive agricultural systems are difficult to expand or transform into more extensive and/or less labor intensive forms due to the limited availability of lower sloping lands (Maharjan et al., 2013; Marquardt et al., 2016). The magnitude of international migration in Nepal suggests that households might not easily be able to use remittances to replace lost labor by hiring wage laborers. Our results suggest that households with access to flatter, more agriculturally suitable lands are able to contract their agricultural activity, choosing to replace lost agricultural labor by investing remittances into labor-saving technologies and maintaining their agricultural production by farming smaller areas more intensively. In contrast, households needing to maintain agricultural production levels on steeper, more marginal areas are unable to adapt their agricultural production system using labor-saving technologies, needing to absorb the loss of labor in some other way, possibly by increasing the amount of agricultural labor of remaining household members to cover the shortfall (see smaller differences in household agricultural activity between high and low migration VDCs in higher sloped areas - Fig. 3B). The result of these contrasting dynamics is an overall reduction in the amount of land dedicated to agriculture on lower, more agriculturally suitable lands. The smaller, but still positive reforestation patterns that we observe at higher slopes could be due to remaining household members needing to spend more time on agricultural activities, and hence less time on forest product extraction activities. This could lead to faster rates of forest regeneration than higher sloped areas with low migration levels. However, we are unable to test these hypotheses with our current dataset.

Second, we present a novel quantitative analytical approach to the study of forest transitions. Our analysis relies entirely on the use of publicly available national and global datasets that are part of either continuous or periodic data collection efforts. In doing so, our study responds to wider calls to make use of such datasets and analytical techniques to assess livelihood and environmental outcomes in the context of emerging global sustainability agendas (Baylis et al., 2016; Hicks et al., 2016; Jagger and Rana, 2017; Oldekop et al., 2016; Sims and Alix-Garcia, 2017). Although quasi-experimental analyses in environment-related fields have predominantly focused on evaluating the effect of conservation and development policies such as protected areas (Canavire-Bacarreza and Hanauer, 2013), we have applied them to the study of social processes and their links to environmental change. To better understand the mechanisms, scale and patterns of forest transitions and other socio-environmental relationships, the approach used in this study offers a useful direction for further research.

Although our approach provides insights over large geographical scales, our analysis highlights several issues that require more detailed data and attention than we are able to provide here. For example, our analysis of forest cover change is unable to assess the environmental quality of resurgent forests. Similarly, the relative contributions of national and international migration remain unclear and the mechanisms through which they influence land use changes could differ quite significantly (VanWey et al., 2012). It is also unclear how international migration influences natural resource management initiatives that require a certain amount of human and social capital, such as community forest management, which is widespread in Nepal and linked to conservation gains - or in turn - how such policies influence migration decisions. This is a potentially important dynamic; if international migration weakens community forest management institutions (Robson and Berkes, 2011), which have been linked to conservation gains in Nepal (Fox, 1993; Jackson et al., 1998; Southworth et al., 2012) and elsewhere (Persha et al., 2011), then international migration could become a contributor to deforestation if trends continue. Further, labor migration patterns are often circular (Hecht et al., 2015) and return migrants often bring new skills, knowledge, and financial capital. How these factors are re-invested into agricultural production systems and how they transform forest landscapes (e.g., whether the observed forest transition is sustained over a longer period) requires further consideration and investigation (Hecht et al., 2015).

It also well established that migration decisions are driven by a suite of motivations, and that environmental factors and risk can also play a critical role (Black et al., 2013). Nepal is highly vulnerable to natural hazards - including earthquakes, floods and land slides, which are compounded by anthropogenic activities, including land use changes and broader environmental changes linked to global climate change. While international migration in Nepal is likely to have been predominantly driven by pull factors (Kern and Müller-Böker, 2015), the question of, how natural hazards and climate change are influencing migration decisions and how these decisions, in turn, influence environmental outcomes remains understudied.

Rural sustainable development and conservation initiatives implemented by national governments, international donor agencies and non-governmental organizations such as community forest management, rarely consider the effects of migration on natural resource use. Conservation and development interventions in both Nepal, which focus predominantly on community-based initiatives, may be able to achieve larger impacts by assisting in natural resource and forest governance arrangements in areas where outmigration might have weakened such institutions. More generally, interventions linked to global sustainability agendas such as the Sustainable Development Goals and Aichi targets should be cognizant of the impacts of international migration flows on natural resource dynamics and the environment, particularly for designing concrete solutions to meet calls for resilient sustainable development pathways (Lewis et al., 2015).

Figures and Tables

Table 1: Post-matched logistic regression coefficients, standard errors, significance values, and marginal effects as a percentage change for forest cover change as function of the treatment variable (international migration in 2001) for all three matching procedures

	Coef.	S.E.	P	Marginal effect (increase in likelihood of reforestation)	Marginal effect (as % change of the mean among controls)
Optimal full	0.670	0.118 (0.229)	<0.0001 (0.0036)	0.103	44 %
Propensity Score	0.718	0.166 (0.239)	<0.0001 (0.0027)	0.123	53 %
Mahalanobis	0.336	0.150 (0.155)	0.0258 (0.030)	0.073	30 %

Note: results in parentheses represent clustered standard errors by district. All matching covariates were included in the regressions, including district level effects for optimal full and propensity score matching, but are not presented here. Marginal effects are the average across districts, holding other variables constant at their means. Percentage changes are the marginal effect / mean likelihood of reforestation among matched controls.

Table 2. Direct mediation effects for changes in agricultural activity, poverty and population density

		No migration/slope interaction effect			Slope/migration interaction effect			
Mediator		Est.	95% CI Lower	95% CI Upper	Est.	95% CI Lower	95% CI Upper	P
Δ Agr. activity	ACME	0.006	0.002	0.011	0.007	0.003	0.012	<0.0001
	ADE	0.096	0.058	0.129	0.097	0.059	0.134	<0.0001
	Prop. Mediated	0.061	0.021	0.127	0.063	0.025	0.127	<0.0001
Δ Poverty	ACME	0.0003	-0.003	0.003	0.0002	-0.003	0.004	
	ADE	0.095	0.058	0.129	0.096	0.060	0.135	<0.0001
	Prop. Mediated	0.003	-0.028	0.041	0.002	-0.033	0.038	
Δ Pop. density	ACME	0.007	0.003	0.012	0.007	0.003	0.013	<0.0001
	ADE	0.096	0.058	0.129	0.097	0.060	0.134	<0.0001
	Prop. Mediated	0.067	0.028	0.131	0.070	0.029	0.140	<0.0001

ACME = Average Causal Mediation Effect; ADE = Average Direct Effect.

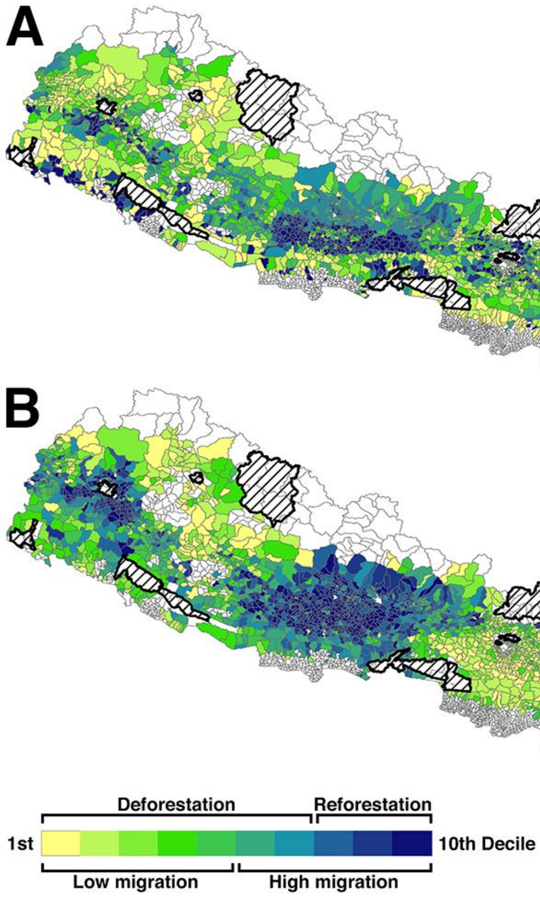

Fig. 1. Forest cover change and levels of international migration in Nepal with each Village Development Committee (VDC) (the unit of analysis) shown as separate areas. (*A*) Forest cover change between 2000 and 2012. (*B*) Levels of international migration estimated using the Nepali 2001 national census data. Data are presented as deciles. Grey areas represent excluded VDCs and hashed areas represent IUCN category I and II protected areas (reasons for exclusion include missing data due to armed conflict, low baseline forest cover, overlap with protected areas and instances of inconsistent data from the Nepali Department of Forests).

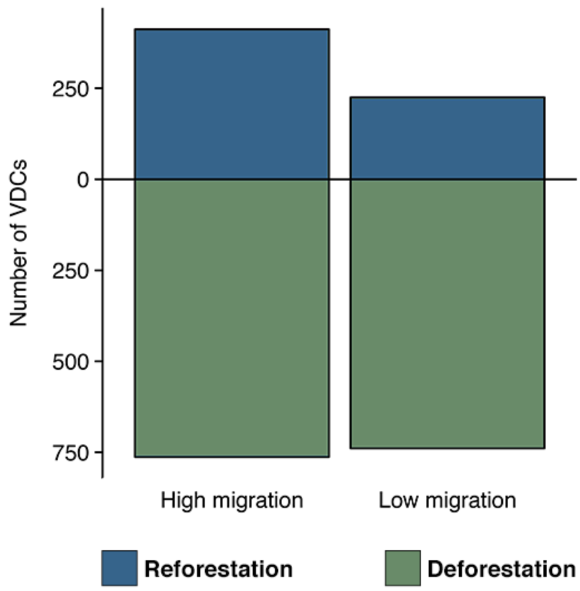

Fig. 2. Number of VDCs in matched sample exhibiting net reforestation and deforestation in areas of high and low migration. Village development committees (VDCs, our unit of analysis) with international outmigration levels above the median in 2001 (high migration) were 44% more likely to experience net reforestation than matched controls with international migration levels below the median (low migration); results from post-matched logistic regression (Table 1). (High migration: 0.251 probability of outmigration; Low migration: 0.053 probability of outmigration). Our matched dataset included 2139 of the 3973 VDCs in Nepal.

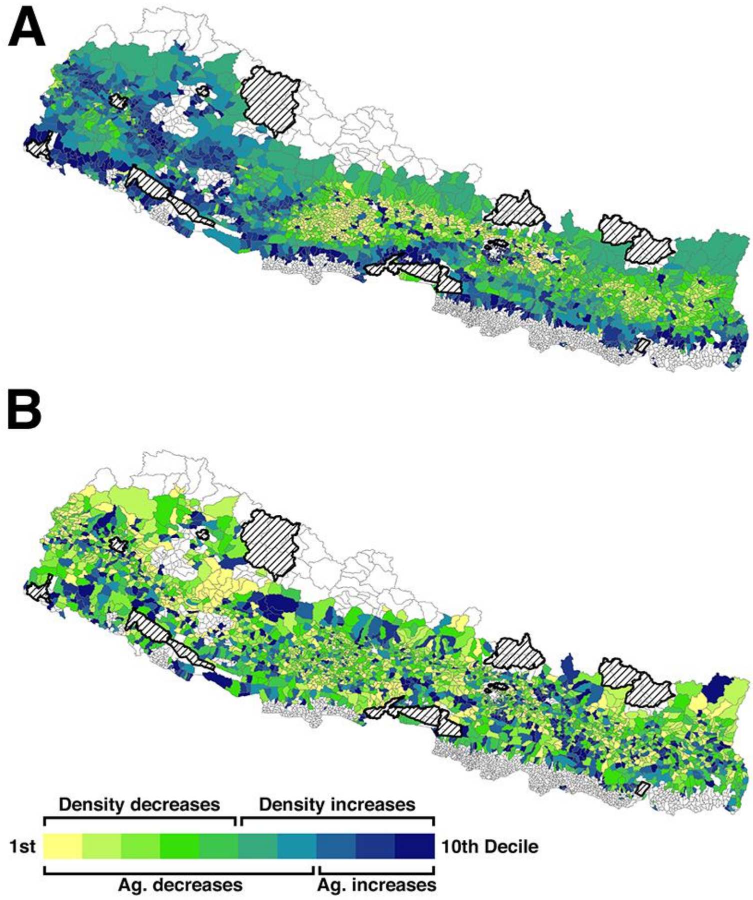

Fig. 3. Changes in population density and agricultural in Nepal with each Village Development Committee (VDC) (the unit of analysis) shown as separate areas. (*A*) Population density changes 2001 and 2011. (*B*) Agricultural estimated using data from the 2001 and 2011 Nepal national census. Data are presented as deciles. Grey areas represent excluded VDCs and hashed areas represent IUCN category I and II protected areas (reasons for exclusion include missing data due to armed conflict, low baseline forest cover, overlap with protected areas and instances of inconsistent data from the Nepali Department of Forests).

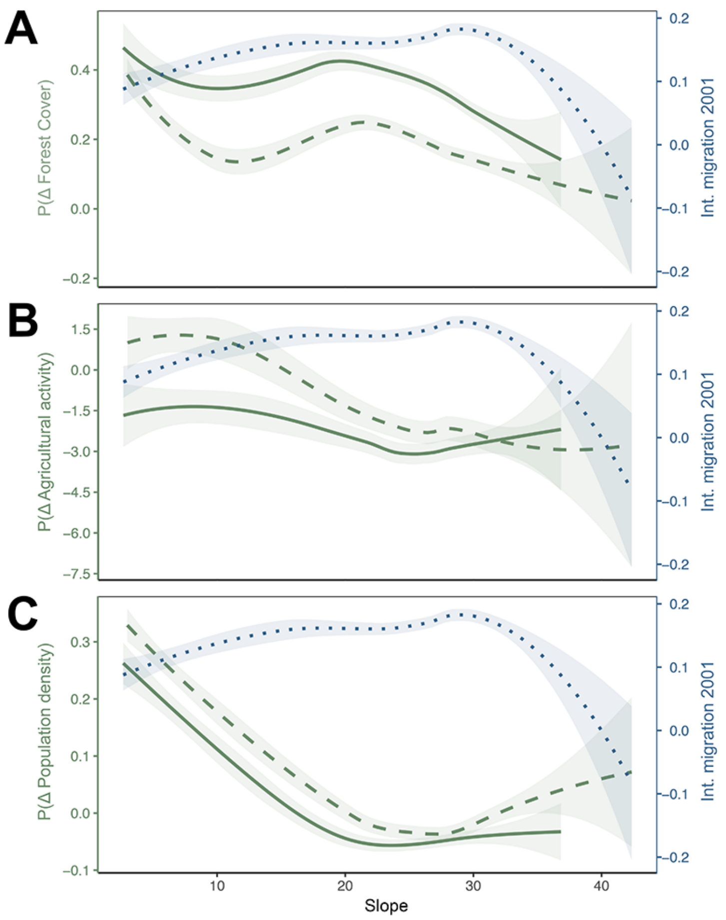

Fig. 4. Levels of international migration in 2001 (dashed blue line; right axis), and predicted probabilities of changes in forest cover (A), agricultural activity (B), and population density (C) for VDCs with high (solid green lines) and low international migration (dashed green lines) along increases in slope. Predicted probabilities were calculated from binomial and linear regressions modeling changes in forest cover, agricultural activity and population density as a function of international migration, remaining mediators and covariates as well as an interaction term between migration and slope using the matched dataset. Results suggest that the effect of international migration on changes in forest cover, agricultural activity and population density is moderated by slope (impacts of international migration were greatest on lower slopes), which we use as a measure of agricultural suitability (Table A8). Lines and 95% confidence intervals (shaded areas) were generated using LOESS smoothing functions.

References

Abel, G.J., Sander, N., 2014. Quantifying Global International Migration Flows. Science 343, 1520–1522.

Acharya, C.P., Leon-Gonzalez, R., 2016. International Remittances, Rural-Urban Migration, and the Quest for Quality Education: The Case of Nepal. National Graduate Institute for Policy Studies, Tokyo.

Aide, T.M., Zimmerman, J.K., Pascarella, J.B., Rivera, L., Marcano Vega, H., 2000. Forest Regeneration in a Chronosequence of Tropical Abandoned Pastures: Implications for Restoration Ecology. Restoration Ecology 8, 328–338.

Alix-Garcia, J., McIntosh, C., Sims, K., 2013. The ecological footprint of poverty alleviation: evidence from Mexico's Oportunidades program. The Review of Economics and Statistics 95, 417-435.

Alkire, S., Santos, M.E., 2014. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. World Development 59, 251–274.

Andam, K.S., Ferraro, P.J., Sims, K.R.E., Healy, A., Holland, M.B., 2010. Protected areas reduced poverty in Costa Rica and Thailand. Proceedings of the National Academy of Sciences 107, 9996–10001.

Angelsen, A., 2010. Policies for reduced deforestation and their impact on agricultural production. Proceedings of the National Academy of Sciences 107, 19639–19644.

Baylis, K., Honey Rosés, J., Börner, J., Corbera, E., Ezzine de Blas, D., Ferraro, P.J., Lapeyre, R., Persson, U.M., Pfaff, A., Wunder, S., 2016. Mainstreaming Impact Evaluation in Nature Conservation. Conservation Letters 9, 58–64.

Bhagwat, S.A., Nogué, S., Willis, K.J., 2014. Cultural drivers of reforestation in tropical forest groves of the Western Ghats of India. Forest Ecology and Management 329, 393–400.

Black, R., Arnell, N.W., Adger, W.N., Thomas, D., Geddes, A., 2013. Migration, immobility and displacement outcomes following extreme events. Environmental Science & Policy 27, S32–S43.

Canavire-Bacarreza, G., Hanauer, M.M., 2013. Estimating the Impacts of Bolivia’s Protected Areas on Poverty. World Development 41, 265–285.

Central Bureau of Statistics, 2011. National Population Census. Government of Nepal, Kathmandu.

Central Bureau of Statistics, 2001. National Population Census. Government of Nepal, Kathmandu.

Davis, B., Carletto, G., Winters, P.C., 2009. Migration, Transfers and Economic Decision Making among Agricultural Households: an Introduction. The Journal of Development Studies 46, 1–13.

Davis, J., Lopez-Carr, D., 2014. Migration, remittances and smallholder decision-making: Implications for land use and livelihood change in Central America. Land Use Policy 36, 319–329.

de Haas, H., 2012. The Migration and Development Pendulum: A Critical View on Research and Policy. International Migration 50, 8–25.

FAO, 2016. Global Forest Resources Assessment 2015. How are the World's Forests Changing? (Second edition). Food and Agriculture Organization of the United Nations.

Fox, J., 1993. Forest Resources in a Nepali Village in 1980 and 1990: The Positive Influence of Population Growth. Mountain Research and Development 13, 89-98.

Geist, H.J., Lambin, E.F., 2002. Proximate Causes and Underlying Driving Forces of Tropical Deforestation Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. BioScience 52, 143–150.

Goerg, G.M., 2015. The Lambert Way to Gaussianize Heavy-Tailed Data with the Inverse of Tukey's h Transformation as a Special Case. The Scientific World Journal 2015, 909231.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853.

Harrell, F.E., Jr, 2016. Package “rms.” The Comprehensive R Archive Network.

Hecht, S., Yang, A.L., Basnett, B.S., Padoch, C., Peluso, N.L., 2015. People in motion, forests in transition: Trends in migration, urbanization, and remittances and their effects on tropical forests (No. 142). Center for International Forestry Research (CIFOR), Bogor, Indonesia.

Hecht, S.B., Saatchi, S.S., 2007. Globalization and Forest Resurgence: Changes in Forest Cover in El Salvador. BioScience 57, 663–672.

Hicks, C.C., Levine, A., Agrawal, A., Basurto, X., Breslow, S.J., Carothers, C., Charnley, S., Coulthard, S., Dolsak, N., Donatuto, J., Garcia-Quijano, C., Mascia, M.B., Norman, K., Poe, M.R., Satterfield, T., Martin, K.S., Levin, P.S., 2016. Engage key social concepts for sustainability. Science 352, 38–40.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25, 1965–1978.

Ho, D., Imai, K., King, G., Stuart, E.A., 2011. MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. Journal of Statistical Software 42, 1–28.

Ho, D.E., Imai, K., King, G., Stuart, E.A., 2007. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. Political Analysis 15, 199–236.

Hobley, M., 2013. Review of 30 Years of Community Forestry in Nepal. Ministry of Forests and Soil Conservation - Government of Nepal.

Imai, K., Keele, L., Tingley, D., Yamamoto, T., 2011. Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies. American Political Science Review 105, 765–789.

Imai, K., Yamamoto, T., 2013. Identification and Sensitivity Analysis for Multiple Causal Mechanisms: Revisiting Evidence from Framing Experiments. Political Analysis 21, 141–171.

IOM, 2014. World Migration Report 2013. International Organization for Migration (IOM), Geneva.

IUCN, UNEP-WCMC, n.d. World Database on Protected Areas. UNEP-WCMC, Cambridge.

Jackson, W., Tamrakar, R., Hunt, S., Shepherd, K., 1998. Land-use changes in two Middle Hills districts of Nepal. Mountain Research and Development 193–212.

Jagger, P., Rana, P., 2017. Using publicly available social and spatial data to evaluate progress on REDD social safeguards in Indonesia. Environmental Science & Policy 76, 59–69.

Joint Research Centre of the European Commission, 2003. Global land cover 2000 database. The Joint Research Centre of the European Commission, Ispra.

Kern, A., Müller-Böker, U., 2015. The middle space of migration: A case study on

brokerage and recruitment agencies in Nepal. Geoforum 65, 158–169.
Kosimidis, I., 2015. Package “brglm.” The Cromprehensive R Archive Network.
Kull, C.A., Ibrahim, C.K., Meredith, T.C., 2007. Tropical Forest Transitions and Globalization:Neo-Liberalism, Migration, Tourism, and International Conservation Agendas. Society & Natural Resources 20, 723–737.
Le, H.D., Smith, C., Herbohn, J., 2014. What drives the success of reforestation projects in tropical developing countries? The case of the Philippines. Global Environmental Change 24, 334–348.
Lewis, S.L., Edwards, D.P., Galbraith, D., 2015. Increasing human dominance of tropical forests. Science 349, 827–832.
MacCallum, R.C., Zhang, S., Preacher, K.J., Rucker, D.D., 2002. On the practice of dichotomization of quantitative variables. Psychological Methods 7, 19–40.
Maharjan, A., Bauer, S., Knerr, B., 2013. International Migration, Remittances and Subsistence Farming: Evidence from Nepal. International Migration 51, 249–263.
Manning, D.T., Taylor, J.E., 2014. Migration and fuel use in rural Mexico. Ecological Economics 102, 126–136.
Marquardt, K., Khatri, D., Pain, A., 2016. REDD+, forest transition, agrarian change and ecosystem services in the hills of Nepal. Human Ecology 44, 229–244.
Meyfroidt, P., 2015. Approaches and terminology for causal analysis in land systems science. Journal of Land Use Science.
Meyfroidt, P., Lambin, E.F., 2012. Prospects and options for an end to deforestation and global restoration of forests. Annual Review of Environment and Resources.
Ministry of Economy, Trade and Industry (METI) of Japan, NASA, S.A., 2011. *Global Digital Elevation Model Version 2*. METI-NASA.
Ministry of Forests and Soil Conservation, 2015. State of Nepal's Forests. Government of Nepal.
Myers, N., Mittermeier, R.A., Mittermeier, C.G., Da Fonseca, G.A.B., Kent, J., 2000. Biodiversity hotspots for conservation priorities. Nature 403, 853–858.
Nagendra, H., 2007. Drivers of reforestation in human-dominated forests. Proceedings of the National Academy of Sciences 104, 15218–15223.
Nelson, A., 2008. Estimated travel time to the nearest city of 50,000 or more people in the year 2000. Joint Research Center of the European Commission, Ispra.
Nelson, A., Chomitz, K.M., 2011. Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods. PLoS ONE 6, e22722.
Oldekop, J.A., Fontana, L.B., Grugel, J., Roughton, N., Adu-Ampong, E.A., Bird, G.K., Dorgan, A., Vera Espinoza, M.A., Wallin, S., Hammett, D., Agbarakwe, E., Agrawal, A., Asylbekova, N., Azkoul, C., Bardsley, C., Bebbington, A.J., Carvalho, S., Chopra, D., Christopoulos, S., Crewe, E., Dop, M.-C., Fischer, J., Gerretsen, D., Glennie, J., Gois, W., Gondwe, M., Harrison, L.A., Hujo, K., Keen, M., Laserna, R., Miggiano, L., Mistry, S., Morgan, R.J., Raftree, L.L., Rhind, D., Rodrigues, T., Roschnik, S., Senkubuge, F., Thornton, I., Trace, S., Ore, T., Valdés, R.M., Vira, B., Yeates, N., Sutherland, W.J., 2016. 100 key research questions for the post-2015 development agenda. Development Policy Review 34, 55–82.
Persha, L., Agrawal, A., Chhatre, A., 2011. Social and Ecological Synergy: Local Rulemaking, Forest Livelihoods, and Biodiversity Conservation. Science 331, 1606–1608.
R Core Team, 2016. *A Language Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna.

Ratha, D., De, S., Plaza, S., Schuettler, K., Shaw, W., Wyss, H., 2016. Migration and Remittances - Recent Developments and Outlook. World Bank, Washington, DC.
Redo, D.J., Redo, D.J., Grau, H.R., Grau, H.R., Aide, T.M., Aide, T.M., Clark, M.L., Clark, M.L., 2012. Asymmetric forest transition driven by the interaction of socioeconomic development and environmental heterogeneity in Central America. Proceedings of the National Academy of Sciences 109, 8839–8844.
Robson, J.P., Berkes, F., 2011. Exploring some of the myths of land use change: Can rural to urban migration drive declines in biodiversity? Global Environmental Change 21, 844–854.
Rudel, T.K., Coomes, O.T., Moran, E., Achard, F., Angelsen, A., Xu, J., Lambin, E., 2005. Forest transitions: towards a global understanding of land use change. Global Environmental Change 15, 23–31.
Schmook, B., Radel, C., 2008. International Labor Migration from a Tropical Development Frontier: Globalizing Households and an Incipient Forest Transition. Human Ecology 36, 891–908.
Sims, K.R.E., Alix-Garcia, J.M., 2017. Parks versus PES: Evaluating direct and incentive-based land conservation in Mexico. Journal of Environmental Economics and Management 86, 8-28.
Sloan, S., Sayer, J.A., 2015. Forest Resources Assessment of 2015 shows positive global trends but forest loss and degradation persist in poor tropical countries. Forest Ecology and Management 352, 134–145.
Southworth, J., Nagendra, H., Cassidy, L., 2012. Forest transition pathways in Asia – studies from Nepal, India, Thailand, and Cambodia. Journal of Land Use Science 7, 51–65.
Stuart, E.A., 2010. Matching Methods for Causal Inference: A Review and a Look Forward. Statistical Science 25, 1–21.
Taylor, M.J., Aguilar-Støen, M., Castellanos, E., Moran-Taylor, M.J., Gerkin, K., 2016. International migration, land use change and the environment in Ixcán, Guatemala. Land Use Policy 54, 290–301.
Tingley, D., Yamamoto, T., Hirose, K., Keele, L., Imai, K., 2014. mediation: R package for causal mediation analysis. Journal of Statistical Software 59.
UNFCCC, 2016. Paris Agreement.
United Nations, 2015. Transforming our world: the 2030 agenda for sustainable development. New York.
VanWey, L.K., Guedes, G.R., D'Antona, Á.O., 2012. Out-migration and land-use change in agricultural frontiers: insights from Altamira settlement project. Popul Environ 34, 44–68.
Whittingham, M.J., Stephens, P.A., Bradbury, R.B., Freckleton, R.P., 2006. Why do we still use stepwise modelling in ecology and behaviour? Journal of Animal Ecology 75, 1182–1189.

Supplementary Material

1. Covariates

1.1. Area

Administrative area size has been previously associated with poverty outcomes and was, hence, included (Andam et al., 2010). Mean VDC size in our sample was 37.4 km^2 (S.D. = 58.2 km^2)

1.2. Baseline forest cover

We expressed VDC baseline forest cover as the proportion of forested area in 2000 with more than 10% tree cover relative to VDC size (FAO, 2016). Given that the UNFAO (FAO, 2016) define of forests as areas with > 10% tree cover, and that Hansen *et al.* (Hansen et al., 2013) use changes of more > 50% tree cover to classify deforestation or reforestation events, we measured baseline forest cover using both > 10% and > 50% thresholds. Both measures were virtually indistinguishable (r = 0.998) and we measured changes in forest cover relative to the > 10% threshold.

1.3. Slope and elevation

Slope and elevation influence agricultural suitability, forest growth, and livelihood decisions (Nelson and Chomitz, 2011). We calculated mean VDC slope and elevation using the ASTER DEM v2 (Ministry of Economy, Trade and Industry (METI) of Japan and NASA, 2011).

1.4. Precipitation

Precipitation affects forest dynamics and we assessed mean precipitation levels in individual VDCs using the WorldClim current precipitation (v1.4, 1950 - 2000) dataset (Hijmans et al., 2005).

1.5. Community forest management

Nepal has a three-decade long history of community forest management (CFM) (Hobley, 2013). CFM can lead to positive environmental and social outcomes (Persha et al., 2011), which might also influence decisions to migrate. We assessed size and age of CFM arrangements in each VDC using the Nepali Department of Forests database on community forest user groups (CFUGs). We used information on community forest size and date of creation for 17553 of the 18321 CFUGs within the database. CFUGs with missing names or missing data on community-managed forests were excluded. The final CFUG set was used to calculate the area under CFM in each VDC relative to VDC size, and the mean number of years since CFM arrangements were set in place. VDCs in which the area under CFM was larger than the VDC size were considered to be measured erroneously and were excluded.

1.6. Poverty

Poverty can influence natural resource use and other livelihood decisions, including migration (Maharjan et al., 2013). We use data from the 2001 and 2011 Nepali national census to generate a widely used and standardized multi-dimensional poverty index (MPI) to assess the incidence of poverty, which we calculated as the proportion of poor households per VDC (Alkire and Santos, 2014). Our index encompasses three dimensions of poverty; health, education and living standards and was adapted to the Nepali context and data consistently available across the censuses.

Our health dimension was composed of 1) child mortality, measured as the proportion of households within each census experiencing one or more child deaths (aged $\leq$ 5 years), and 2) premature mortality, measured as the proportion of households within each census experiencing a death below the period life expectancy.

Our education dimension was composed of 1) school attendance, measured as the proportion of households within each census with a school-aged child (aged 6 - 16 years, the average school leaving certificate completion age) not attending school, and 2) years of schooling, measured as the proportion of households within each census with at least one household member aged $\geq$ 11 years that has not completed 5 years schooling.

Our living standards dimension included the proportion of households within each census using 1) wood or dung as cooking fuel, and the proportion of households without 2) electricity, 3) clean water sources (as defined by the Millenium Development Goals (MDGs)) and 4) improved sanitation (as defined by the MDGs). All three dimensions of poverty were given equal weighting. We use the MPI to measure poverty levels in 2001 (baseline) as well as changes in 2001 – 2011 poverty, which were included in our mediator analysis. Missing data were treated in the same way as in Alkire and Santos (2014). Households for which all members had missing data in any indicator were excluded. If data was missing for only some members, the data were treated as follows:

1.6.1. Health

If information on mortality was missing, the household was excluded.

1.6.2. Years of schooling

If at least one member had five or more years of education the household was classified as non-deprived in that dimension. If information was available for at least two-thirds of household members, with each having < 5 years of education the household was classified as deprived in that dimension. Otherwise the household was excluded.

1.6.3. School attendance

If information was available for at least one child in the household, the household was classified accordingly otherwise it was excluded.

1.6.4. Livelihood standards

If households had missing data on any livelihood standard indicators were excluded.

1.7. Population density

Population pressure is linked to resource overexploitation, and can act as a driver of outmigration as people seek to out less degraded areas (Geist and Lambin, 2002). We use the Nepali national census to measure VDC population density in 2001 (baseline), and 2001 – 2011 population density changes, which we used in our mediator analysis

1.8. Agricultural activity

Agriculture is a leading cause of land-cover change and deforestation, globally (Geist and Lambin, 2002). The Nepali national census provides no information on land use or consistent information on land holdings. Instead, we use the number of months that household members above school age (> 16 years of age) and below pension age (< 60) dedicate to agriculture (expressed as the total number of months within a VDC divided by the number of sampled households) as a measure of agricultural activity. We purposefully excluded school- and pension-aged household members from our analysis because households might not respond truthfully about the amount of time that pension-eligible household members or those that should be school spend working in agriculture or other forms of employment.

Agriculture in Nepal is predominantly low-intensity small-scale agriculture (*9*). Although our measure does not account for changes in agricultural intensification, we believe it can act as a reliable proxy for land-use and use it to measure agricultural activity in 2001 (baseline) and 2001 – 2011 changes in agricultural activity, which we used in our mediator analysis. Nonetheless, to ensure that migration is also linked to changes in other measures of land use we analyze the effect of migration on the proportion of land that households dedicated to agriculture and their probability of having land in fallow using a separate panel dataset of 3949 households (see robustness checks below).

1.9. Travel time to population and administrative centers

Access to markets, services (e.g., technical assistance) and transport nodes can significantly influence land-use, and other livelihood decisions including migration (Geist and Lambin, 2002). We adapted the European Commission's Joint Research Centre's (JRC) travel time to major cities algorithm (Nelson, 2008) to measure travel time to district headquarters and population centers with ≥10,000 and ≥50,000 inhabitants using the Nepali Survey Departments road data, the JRC's global land cover database (Joint Research Centre of the European Commission, 2003), and the ASTER DEM v2 (Ministry of Economy, Trade and Industry (METI) of Japan and NASA, 2011), which we used to compute elevation and slope correction factors. We used VDC centroids as points of departure for all calculations.

1.10. Administrative areas

Districts in Nepal are the administrative level above VDC. We included District as a covariate because they have significant decision-making autonomy, and because most donor-funded interventions are administered at the District-level. Regressions with District controls account for these and other important unobserved factors that are fixed over time but vary across Districts.

2. Robustness checks

In addition to different forms of matching, we conducted an additional six robustness tests to confirm the validity of our results:

First, as an alternative to our matching approach we conducted a standard binomial regression modeling forest cover change as a function of our continuous estimates of migration levels in 2001 and all covariates; i.e. fitted a full model (Whittingham et al., 2006). Results from this analysis confirmed that using standard regression techniques did not affect our principal finding that international outmigration was a significant driver of reforestation (logit coef. = 0.180, S.E. = 0.079, P = 0.0231).

Second, given the time lag between treatment (international migration in 2001) and outcome (forest cover change 2000 - 2012), and the potential for spatial changes in 2001 – 2011 migration patterns to affect forest cover change during the same time period, we confirmed that the observed trends in 2001 continue throughout the decade. To do so, we first ran a correlation between our national census derived estimates of international migration levels in 2001 and 2011, showing that although international migration levels during the decadal interval almost doubled ($\mu_{(2001)}$ = 0.154; $\mu_{(2011)}$ = 0.286), areas of higher international migration in 2001 continued to be areas of higher international migration in 2011 (r = 0.715, P < 0.0001). Next, we ensured that these observed increases in international migration were also linked to increases in forest cover. We converted 2001 - 2011 changes in international migration into a binary treatment variable, classifying migration changes as “high” (≥ median) or “low” (≤ median). We then generated a balanced matched dataset that included all the previous covariates as well as migration levels at baseline in 2001 (Figure A4, Table A4). Post-matching regression results confirm that increases in international migration were also positively and significantly associated with increases in forest cover (logit coef. = 0.714, S.E. = 0.124, P < 0.0001). Furthermore, we also plotted the cumulative increase in migration and deforestation between 2000 and 2012 using data from the 2011 census data, which contains information on duration of migration, and the high-resolution forest cover change dataset v1.0’s (Hansen et al., 2013) deforestation by year data (reforestation data is not available by year). Rates of migration increase between 2001 and 2011 in our unmatched dataset were higher for areas classified as high-migration in 2001, and rates of deforestation between 2000 and 2012 were lower in areas of high migration, providing additional evidence that our result is not period dependent (Fig. A8).

Third, we ensured that the observed effects of migration on forest cover change are not due to our choice of outcome variable, which we transformed into a binary variable representing either net deforestation or reforestation because it did not meet assumptions of normality (MacCallum et al., 2002). To do so, we first transformed our continuous forest cover change variable using a Lambert W transformation (Goerg, 2015) and ran a linear regression using our matched dataset modeling our transformed forest cover change variable as a function of migration in 2001 and our full list covariates. Results from this regression confirmed that international migration in 2001 led to significant reforestation in Nepal (coef. = 0.001, $P < 0.0001$). Next, we separately assessed the effect of migration in 2001 on gross levels of both reforestation and deforestation using only the forest gain and loss layers available as part of the high-resolution forest cover change dataset (Hansen et al., 2013). We excluded VDCs with no gross forest gain or loss and log transformed our reforestation and deforestation variables to correct for non-normal distributions. We then created matched datasets using optimal full matching and our treatment variable for migration levels in 2001 (Figures A5-A6 and Tables A5-A6). Post-matching regressions confirm that migration in 2001 led to increases in reforestation (coef. = 0.200, S.E. = 0.049, $P < 0.0001$) and decreases in deforestation (coef. = -0.192, S.E. = 0.042, $P < 0.0001$), and that our results are not dependent on our choice of outcome variable. Finally, we conduct a matched binomial regression using our dichotomized forest cover change variable but exclude VDCs exhibiting no net forest cover change (n = 118). We find that removing these cases from our analysis has little overall effect on our principal outcome (logit coef. = 0.920, clustered standard errors = 0.257, P = 0.0003).

Fourth, we ensure that the effect of migration on forest cover is not dependent upon the exclusion of VDCs with low baseline forest cover. We created a balanced matched dataset using baseline levels of international migration (2001) as treatment variable (Figure A7, Table A7) that also included all VDCs with low baseline forest cover (i.e. those with <5% original forest cover, n = 3742 VDCs). Post-matching regression results confirmed that migration in 2001 lead to increases in reforestation (coef. = 0.385, S.E. = 0.095, $P < 0.0001$) and that our principal result is not dependent upon exclusion of VDCs with low baseline forest cover.

Fifth, we confirmed that the observed effects of international migration on forest cover change occurred regardless of any co-linearity between international and national migration. National migration levels could not be included as a matching covariate because they can only be calculated at the District level using the Nepali national census. We defined national migration as an individual's move from one District to another within the last 5 years because the mean length of stay of international migrants in destination countries in 2001 was 4.72 years. National and international migration at the District-level were moderately and positively correlated (n = 74, r = 0.429). To ensure that effects of international migration occurred irrespective of their relationship with national migration levels we conducted two separate analyses. First, we constructed a district-level dataset (n = 74) and ran alternate binomial regressions modeling forest cover change as a function of either national or international migration. Results from this regression confirm a positive and marginally statistically significant effect of international migration on forest cover change (probit coef. = 0.401, P = 0.0432) and a negative but non-statistically significant effect of national migration on forest cover change (probit coef. = -0.039, P = 0.873).

We also tested that the effect of migration persisted in instances of lower correlation levels between internal and international outmigration. We used a Monte Carlo style approach, running a series of unmatched logistic regressions modeling forest cover change as a function of international migration levels in 2001 (continuous variable) and all covariates (excluding district). The data for these regressions was generated by repeatedly sampling and analyzing (n=983 simulations) a random set of 37 districts (half the number of districts included in our full dataset) with weak correlations between national and international migration ($r \leq 0.25$). The mean regression coefficient for international outmigration in 2001 was positive (mean logit coef. = 0.318, S.E. = 0.001) and statistically significant (mean P = 0.011, S.E. = 0.002), suggesting that the effect of international migration on forest cover change occurs irrespective of its relationship with national migration levels. Inclusion of District fixed effects in these models using similar subsets of data (n = 966 simulations) with weak correlations between migration types showed a positive (mean logit coef. = 0.132, S.E. = 0.003) but non-significant effect of international migration (mean P = 0.319, S.E. = 0.009). However, an analogous analysis with subsets (n = 1535 simulations) of data with strong correlations ($r \geq 0.65$) between migration types produced similar positive (mean logit coef. = 0.198, S.E. = 0.003) but non-significant results (mean P = 0.177, S.E. = 0.006). Collectively, these results confirm that the effect of international migration on forest cover change occurs irrespective of its relationship to national migration but that the strength of the international migration effect is dependent on District-level effects, which we control for in all matching-based analyses.

Finally, we confirm that household levels of international migration influence a wider range of agricultural production measures that could provide a direct link to forest transitions, and that these are also mediated by the effect of slope. We do so using a separate panel dataset for the years 2012 and 2015 of 3949 rural households in 23 districts, which was collected as part of a separate project to assess the impacts of Nepal's Multi-Stakeholder Forestry Program (MSFP). The dataset includes basic household-level information on a similar set of variables used for our measures of multi-dimensional poverty using the census data as well as agricultural production and number of international and national migrants (additional information about the dataset and these variables are available upon request). We focused on changes between 2012-2015 of three measures of agricultural production: (i) change in the amount of irrigated and partially-irrigated land, which are predominantly used for the cultivation of commercial crops; (ii) change in the amount agricultural inputs as a proportion of the amount of land cultivated (e.g., seeds, fertilizer and other agricultural costs); change in the amount of hired agricultural labor as a proportion of the amount of land cultivated.

Histograms of data from all three measures suffered from high levels of kurtosis and we were only able to successfully transform our measure of cultivated land. Our measures of change in the use of agricultural inputs and hired agricultural labor were transformed into dichotomized variables (increase or decrease/no change) (16). All three measures were modeled in post-matching (Tables A11 and A12) regressions using a binary international migration in 2012 variable (households with more than two international migrants in 2012 versus households with one or fewer migrants - we use this specification to match our high versus low migration in our main analysis), improved sanitation, access to clean water, electricity, house construction materials, household assets, years of schooling, school attendance, amount of irrigated and partially-irrigated land in 2012, total land dedicated to agriculture in 2012 (several yearly rotations), travel time to the nearest all weather road, district, participation in the development intervention in question, and international migration and slope interaction term. Slope values were calculated at the level of the VDC and correspond to the same average VDC slope values used in our principal analysis. Households with missing data were excluded from the analysis.

For binomial regressions measuring changes in the use of agricultural inputs and labor, we used the *brglm* function of the ‘brglm’ package (Kosimidis, 2015), which uses Firth bias-reduction methods to deal with instances of near perfect data separation. For these regressions we also removed households with no irrigated and partially-irrigated land in 2012.

Results from these three regressions show a significant moderating effect of slope on the effect of international migration on changes in both the amount of irrigated and partially-irrigated land dedicated to agriculture and changes in the amount of agricultural inputs (Table A13). Households with international migrants on lower slopes experienced larger reductions in the amount of irrigated and partially-irrigated land as well as larger increases in the amount of agricultural inputs (Fig. A9). We found no statistically significant effect of international migration on the changes in the amount of hired labor. These results suggest that households with international migrants in lower sloped areas are intensifying their agricultural production, leading to an overall reduction in the amount of land dedicated to agriculture. Our results also suggest that households with international remittances are investing remittances in labor-saving technologies rather than in the replacement of lost agricultural labor, confirming the agricultural activity reduction patterns that we observe in our mediator analysis.

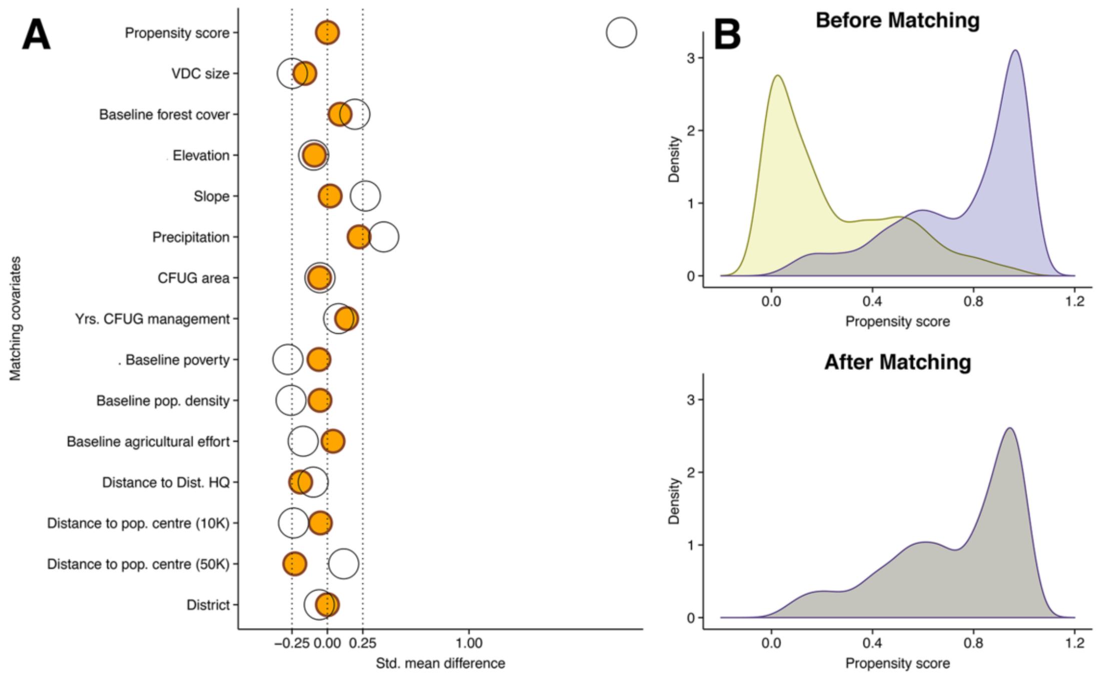

Fig. A1. Covariate balance before and after optimal full matching using levels of migration in 2001 as treatment. (*A*) Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles). Balance results for District are presented as means across all Districts. (*B*) Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey). Matching resulted in a near perfect overlap in propensity scores.

Table A1. Covariate balance before and after optimal full matching using levels of international migration in 2001 as treatment

	Before Matching			After Matching		
	Means Treated *(n = 1364)*	Means Control *(n = 1362)*	Stand. Mean Diff.	Means Treated *(n = 1175)*	Means Control *(n = 964)*	Stand. Mean Diff.
Propensity score	0.760	0.241	2.077	0.722	0.722	0.000
VDC Size	3170.489	4307.955	-0.247	3378.051	4110.379	-0.159
Baseline forest cover	0.515	0.475	0.194	0.511	0.492	0.090
Elevation	1304.923	1368.671	-0.097	1308.647	1368.937	-0.092
Slope	24.110	22.373	0.269	23.926	23.798	0.020
Precipitation	150.939	135.191	0.398	146.478	137.611	0.224
CFUG area	0.174	0.182	-0.052	0.178	0.187	-0.055
Yrs. CFUG management	11.353	10.941	0.080	11.218	10.514	0.136
Baseline poverty	0.560	0.613	-0.279	0.583	0.594	-0.060
Baseline population density	2.170	2.526	-0.256	2.092	2.165	-0.053
Baseline agricultural activity	13.220	14.022	-0.171	13.527	13.341	0.040
Distance to Dist. HQ	3.832	4.113	-0.100	3.976	4.504	-0.189
Distance to pop. centre 10K	4.728	5.534	-0.239	4.773	4.940	-0.049
Distance to pop. centre 50K	11.974	11.060	0.115	12.375	14.201	-0.230
District[§]	0.018	0.013	-0.057	0.018	0.018	0.000

[§] Data are presented as the mean across all Districts

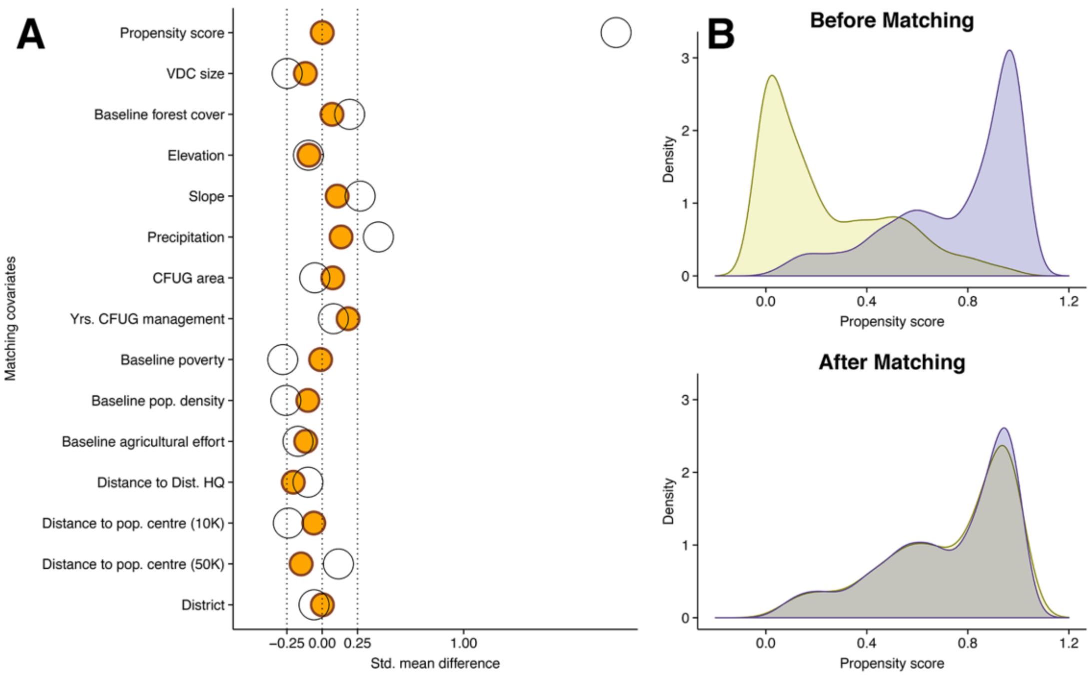

Fig. A2. Covariate balance before and after propensity score matching using international migration levels in 2001 as treatment. (*A*) Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles). Balance results for District are presented as means across all Districts. (*B*) Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey). Matching resulted in much improved overlap in propensity scores.

Table A2. Covariate balance before and after propensity score matching using international levels of migration in 2001 as treatment

	Before Matching			After Matching		
	Means Treated *(n = 1364)*	Means Control *(n = 1362)*	Stand. Mean Diff.	Means Treated *(n = 1175)*	Means Control *(n = 359)*	Stand. Mean Diff.
Propensity score	0.760	0.241	2.077	0.722	0.722	0.000
VDC Size	3170.489	4307.955	-0.247	3378.051	3924.050	-0.119
Baseline forest cover	0.515	0.475	0.194	0.511	0.496	0.070
Elevation	1304.923	1368.671	-0.097	1308.647	1369.900	-0.093
Slope	24.110	22.373	0.269	23.926	23.240	0.106
Precipitation	150.939	135.191	0.398	146.478	141.191	0.134
CFUG area	0.174	0.182	-0.052	0.178	0.167	0.075
Yrs. CFUG management	11.353	10.941	0.080	11.218	10.270	0.183
Baseline poverty	0.560	0.613	-0.279	0.583	0.585	-0.011
Baseline population density	2.170	2.526	-0.256	2.092	2.232	-0.101
Baseline agricultural activity	13.220	14.022	-0.171	13.527	14.074	-0.117
Distance to Dist. HQ	3.832	4.113	-0.100	3.976	4.548	-0.204
Distance to pop. centre 10K	4.728	5.534	-0.239	4.773	4.974	-0.059
Distance to pop. centre 50K	11.974	11.060	0.115	12.375	13.557	-0.149
District[§]	0.018	0.013	-0.057	0.018	0.018	0.001

[§] Data are presented as the mean across all Districts

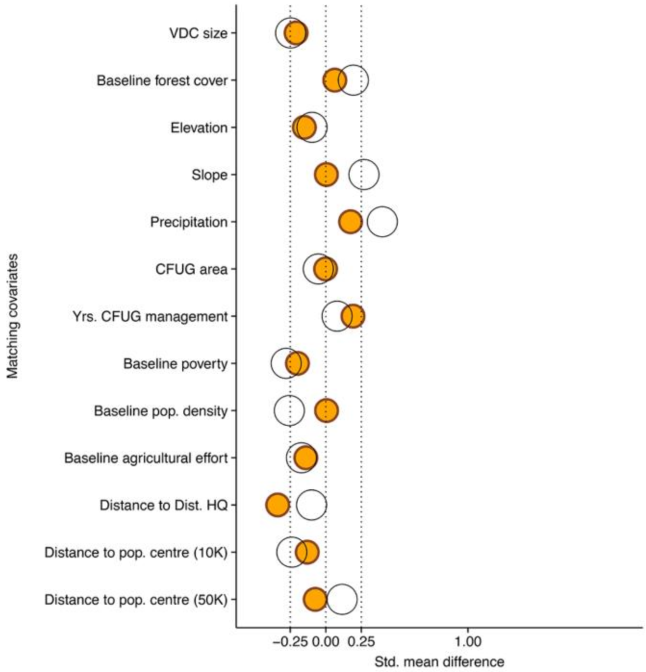

Fig. A3. Covariate balance before and after Mahalanobis distance matching using international migration levels in 2001 as treatment. Standardized mean difference for all matching covariates before (open circles) and after matching (orange circles).

Table A3. Covariate balance before and after Mahalanobis distance matching using levels of international migration in 2001 as treatment

	Before Matching			After Matching		
	Means Treated *(n = 1364)*	Means Control *(n = 1362)*	Stand. Mean Diff.	Means Treated *(n = 1175)*	Means Control *(n = 964)*	Stand. Mean Diff.
VDC Size	3170.489	4307.955	-0.247	3241.764	4201.078	-0.209
Baseline forest cover	0.515	0.475	0.194	0.511	0.497	0.063
Elevation	1304.923	1368.671	-0.097	1317.352	1416.457	-0.151
Slope	24.110	22.373	0.269	24.111	24.085	0.004
Precipitation	150.939	135.191	0.398	148.663	141.760	0.174
CFUG area	0.174	0.182	-0.052	0.177	0.177	-0.001
Yrs. CFUG management	11.353	10.941	0.080	11.240	10.248	0.191
Baseline poverty	0.560	0.613	-0.279	0.568	0.606	-0.199
Baseline population density	2.170	2.526	-0.256	2.125	2.117	0.006
Baseline agricultural activity	13.220	14.022	-0.171	13.200	13.857	-0.140
Distance to Dist. HQ	3.832	4.113	-0.100	3.891	4.840	-0.338
Distance to pop. centre 10K	4.728	5.534	-0.239	4.790	5.231	-0.130
Distance to pop. centre 50K	11.974	11.060	0.115	12.344	12.930	-0.074

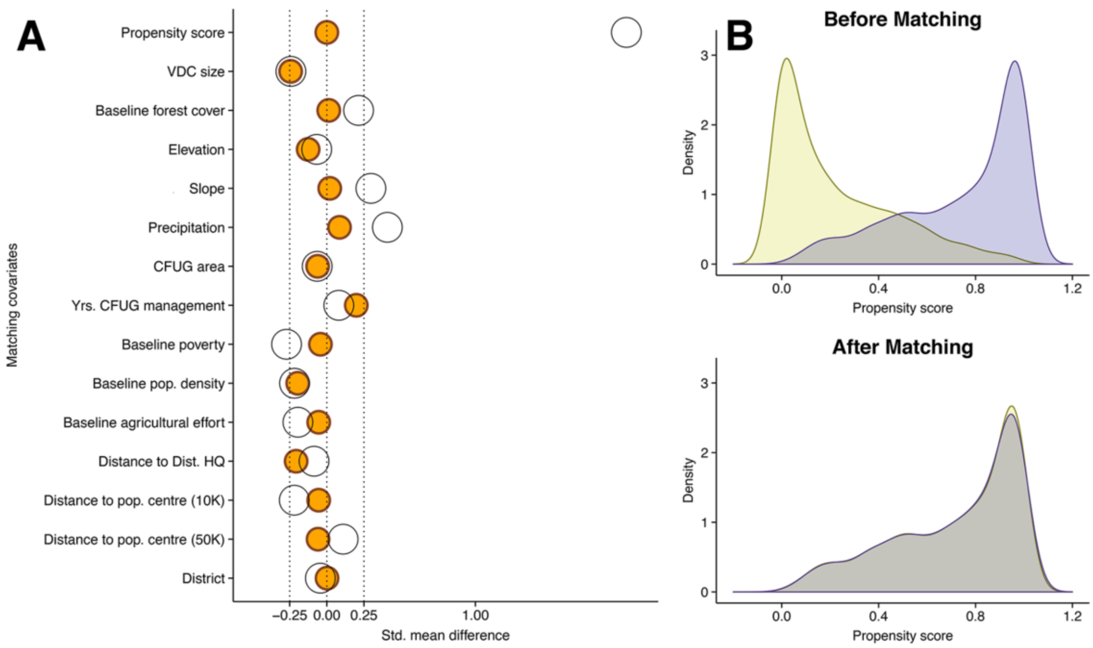

Fig. A4. Covariate balance before and after optimal full matching using change in migration between 2001 and 2011 as treatment. (*A*) Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles). Balance results for District are presented as means across all Districts. (*B*) Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey). Matching resulted in much improved overlap in propensity scores.

Table A4. Covariate balance before and after optimal full matching using international changes in migration between 2001 and 2011 as treatment

	Before Matching			After Matching		
	Means Treated *(n = 1364)*	Means Control *(n = 1362)*	Stand. Mean Diff.	Means Treated *(n = 1142)*	Means Control *(n = 1028)*	Stand. Mean Diff.
Propensity score	0.746	0.226	2.016	0.715	0.715	0.000
VDC Size	3142.743	4267.995	-0.242	3307.174	4439.292	-0.243
Baseline forest cover	0.518	0.474	0.214	0.511	0.508	0.013
Elevation	1313.153	1357.744	-0.068	1314.314	1396.761	-0.126
Slope	24.236	22.359	0.297	24.121	23.998	0.020
Precipitation	151.722	135.390	0.408	147.578	144.154	0.086
CFUG area	0.172	0.182	-0.065	0.179	0.188	-0.062
Yrs. CFUG management	11.368	10.951	0.081	11.279	10.254	0.198
Baseline poverty	0.559	0.611	-0.271	0.578	0.586	-0.043
Baseline population density	2.187	2.491	-0.218	2.123	2.396	-0.196
Baseline agricultural activity	13.147	14.041	-0.195	13.288	13.540	-0.055
Distance to Dist. HQ	3.844	4.087	-0.086	3.951	4.534	-0.207
Distance to pop. centre 10K	4.740	5.478	-0.219	4.794	4.978	-0.055
Distance to pop. centre 50K	11.978	11.108	0.110	12.489	12.959	-0.059
District[§]	0.018	0.013	-0.043	0.018	0.018	0.001

[§] Data are presented as the mean across all Districts

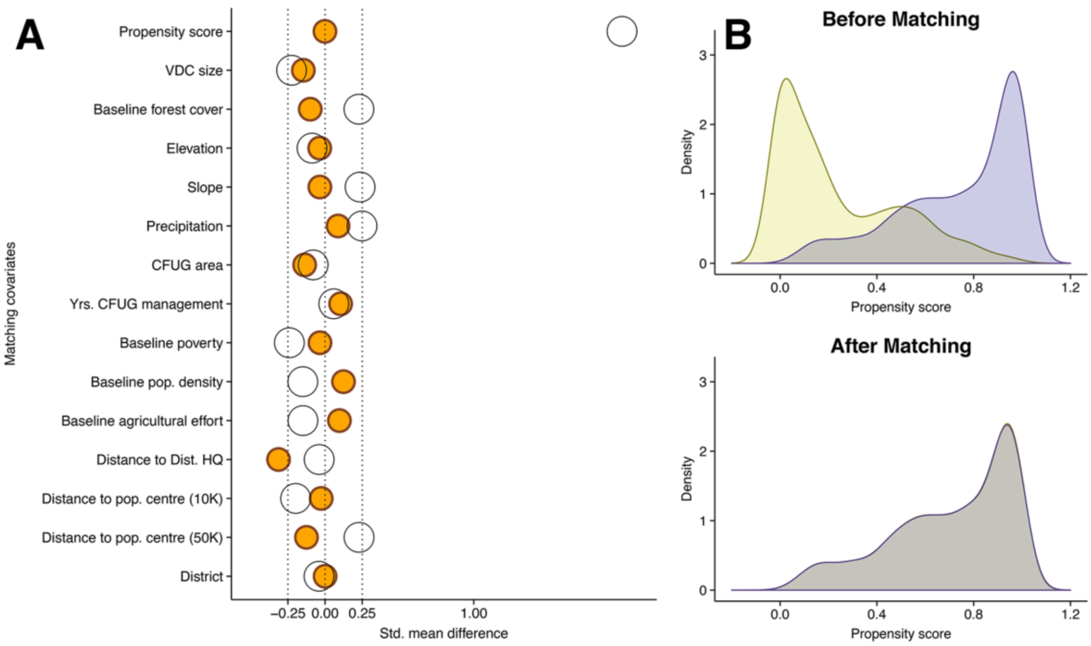

Fig. A5. Covariate balance before and after optimal full matching using international migration in 2001 as treatment and the gross reforestation dataset. (*A*) Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles). Balance results for District are presented as means across all Districts. (*B*) Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey). Matching resulted in near perfect overlap in propensity scores.

Table A5. Covariate balance before and after optimal full matching using international migration in 2001 and the gross reforestation data

	Before Matching			After Matching		
	Means Treated *(n = 1364)*	Means Control *(n = 1362)*	Stand. Mean Diff.	Means Treated *(n = 1019)*	Means Control *(n = 906)*	Stand. Mean Diff.
Propensity score	0.744	0.241	1.997	0.706	0.706	-0.001
VDC Size	3422.206	4522.653	-0.225	3577.531	4292.366	-0.146
Baseline forest cover	0.537	0.489	0.228	0.529	0.550	-0.100
Elevation	1315.587	1375.222	-0.088	1331.677	1356.180	-0.036
Slope	24.107	22.575	0.235	24.043	24.272	-0.035
Precipitation	144.633	136.021	0.249	140.115	137.082	0.088
CFUG area	0.171	0.183	-0.080	0.175	0.196	-0.138
Yrs. CFUG management	11.307	11.001	0.058	11.285	10.738	0.105
Baseline poverty	0.578	0.623	-0.240	0.599	0.606	-0.034
Baseline population density	2.052	2.240	-0.150	1.937	1.781	0.124
Baseline agricultural activity	13.479	14.192	-0.149	13.698	13.235	0.097
Distance to Dist. HQ	4.052	4.167	-0.040	4.165	5.067	-0.313
Distance to pop. centre 10K	4.674	5.340	-0.198	4.722	4.810	-0.026
Distance to pop. centre 50K	12.787	10.974	0.229	13.281	14.274	-0.125
District[§]	0.018	0.013	-0.041	0.018	0.018	0.000

[§] Data are presented as the mean across all Districts

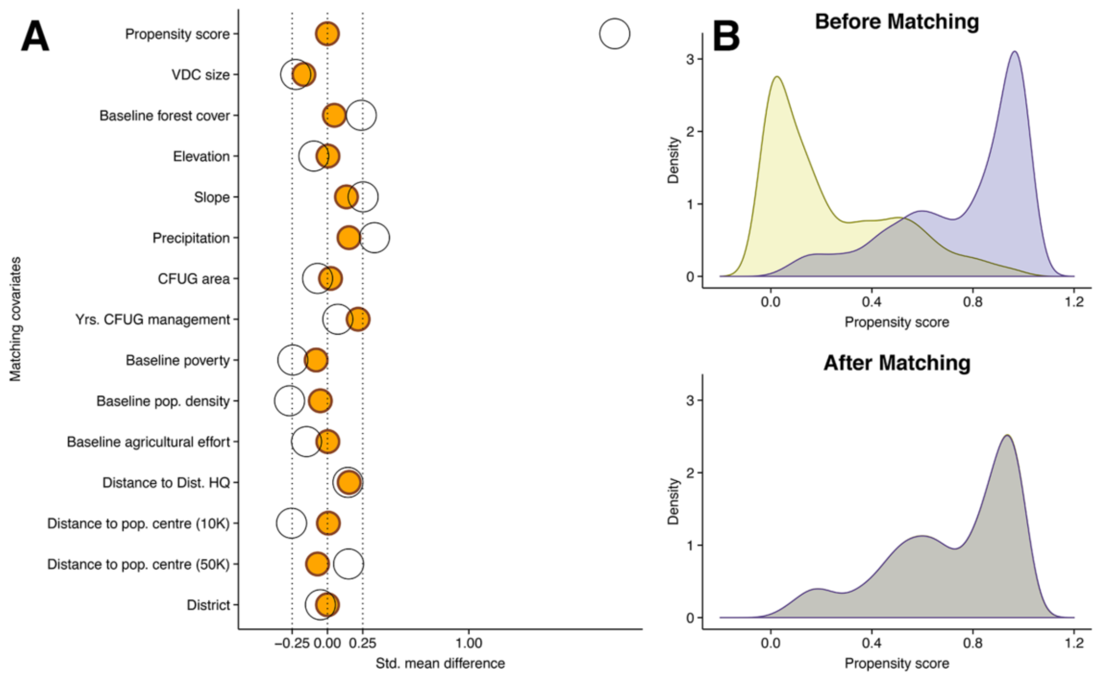

Fig. A6. Covariate balance before and after optimal full matching using international migration in 2001 as treatment and the gross deforestation dataset. (*A*) Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles). Balance results for District are presented as means across all Districts. (*B*) Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey). Matching resulted in a near perfect overlap in propensity scores.

Table A6. Covariate balance before and after optimal full matching using international migration in 2001 and the gross deforestation data

	Before Matching			After Matching		
	Means Treated *(n = 1364)*	Means Control *(n = 1362)*	Stand. Mean Diff.	Means Treated *(n = 1019)*	Means Control *(n = 906)*	Stand. Mean Diff.
Propensity score	0.748	0.240	2.033	0.713	0.713	0.000
VDC Size	3312.160	4372.914	-0.224	3534.692	4322.285	-0.167
Baseline forest cover	0.528	0.479	0.239	0.517	0.507	0.049
Elevation	1307.831	1372.675	-0.097	1323.122	1320.561	0.004
Slope	24.105	22.451	0.252	23.901	23.020	0.135
Precipitation	147.752	135.149	0.333	144.048	138.267	0.153
CFUG area	0.172	0.183	-0.070	0.178	0.174	0.022
Yrs. CFUG management	11.343	10.958	0.073	11.318	10.181	0.217
Baseline poverty	0.570	0.616	-0.245	0.589	0.604	-0.080
Baseline population density	2.084	2.437	-0.268	1.996	2.063	-0.051
Baseline agricultural activity	13.341	14.044	-0.148	13.558	13.544	0.003
Distance to Dist. HQ	4.199	3.665	0.145	4.285	3.718	0.154
Distance to pop. centre 10K	4.679	5.544	-0.254	4.754	4.731	0.007
Distance to pop. centre 50K	12.299	11.106	0.150	12.557	13.113	-0.070
District[§]	0.018	0.013	-0.050	0.018	0.018	0.000

[§] Data are presented as the mean across all Districts

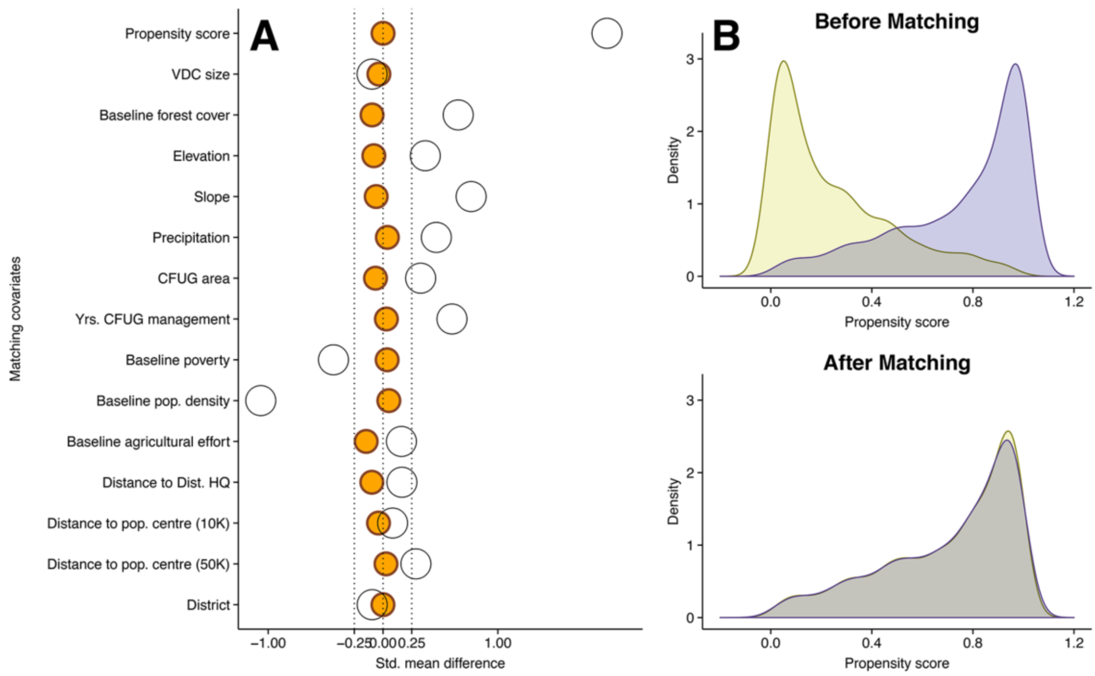

Fig. A7. Covariate balance before and after optimal full matching using international migration in 2001 as treatment and the dataset including VDCs with < 5% baseline forest cover. (*A*) Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles). Balance results for District are presented as means across all Districts. (*B*) Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey). Matching resulted in much improved overlap in propensity scores.

Table A7. Covariate balance before and after optimal full matching using international migration in 2001 and the gross deforestation data

	Before Matching			After Matching		
	Means Treated *(n = 1871)*	Means Control *(n = 1871)*	Stand. Mean Diff.	Means Treated *(n = 1753)*	Means Control *(n = 1564)*	Stand. Mean Diff.
Propensity score	0.754	0.247	1.950	0.705	0.705	0.000
VDC Size	3101.869	3522.087	-0.096	3299.060	3456.963	-0.036
Baseline forest cover	0.446	0.280	0.655	0.428	0.452	-0.096
Elevation	1178.835	895.151	0.368	1154.133	1215.748	-0.080
Slope	21.600	14.692	0.767	20.820	21.355	-0.059
Precipitation	146.761	128.801	0.464	140.877	139.417	0.038
CFUG area	0.158	0.106	0.328	0.153	0.164	-0.066
Yrs. CFUG management	10.383	6.834	0.601	10.142	9.970	0.029
Baseline poverty	0.570	0.653	-0.432	0.594	0.587	0.036
Baseline population density	2.635	5.020	-1.065	2.596	2.483	0.051
Baseline agricultural activity	12.780	12.000	0.160	13.025	13.739	-0.147
Distance to Dist. HQ	3.641	3.147	0.165	3.711	4.005	-0.098
Distance to pop. center 10K	4.392	4.067	0.083	4.331	4.485	-0.039
Distance to pop. center 50K	11.175	8.823	0.286	11.324	11.113	0.026
District[§]	0.013	0.013	-0.100	0.013	0.013	-0.001

[§] Data are presented as the mean across all Districts

Table A8. Post-matched regression coefficients, standard errors and significance values for forest cover change as a function of the treatment variable (international migration in 2001), and the three mediator variables as a function of the treatment variable (international migration in 2001) and remaining mediators

		No interaction effect			Interaction effect		
		Coef.	S.E.	P	Coef.	S.E.	P
Δ Forest cover	Migration[High]	0.670	0.118	<0.0001	1.695	0.441	0.0001
	Slope	-0.010	0.020	0.596	0.017	0.023	0.447
	Migration[High]* Slope				-0.043	0.018	0.016
	[Res. Deviance]	[2043.5]			[2037.6]		
	[AIC]	[2112.5]			[2109.2]		
Δ Agr. activity	Migration[High]	-0.440	0.116	0.0002	-1.598	0.409	<0.0001
	Slope	-0.001	0.019	0.952	-0.030	0.021	0.156
	Migration[High]* Slope				0.048	0.016	0.0032
	Δ Population density	-1.606	0.416	0.0001	-1.666	0.415	<0.0001
	Δ Poverty	1.834	0.580	0.0016	1.731	0.580	0.0029
	[Adj. R^2]	[0.749]			[0.750]		
Δ Poverty	Migration[High]	-0.016	0.004	0.0002	-0.054	0.016	0.0005
	Slope	0.002	0.001	0.000	0.002	0.001	0.048
	Migration[High]* Slope				0.002	0.001	0.011
	Δ Pop. density	0.005	0.016	0.770	0.002	0.016	0.879
	Δ Agr. effort	0.003	0.001	0.002	0.002	0.001	0.003
	[Adj. R^2]	[0.560]			[0.571]		
Δ Pop. density	Migration[High]	-0.024	0.006	0.0001	-0.075	0.022	0.001
	Slope	-0.002	0.001	0.020	-0.004	0.001	0.001
	Migration[High]* Slope				0.002	0.001	0.013
	Δ Agr. effort	-0.004	0.001	0.0001	-0.005	0.001	<0.0001
	Δ Poverty	0.009	0.031	0.770	0.005	0.031	0.879
	[Adj. R^2]	-0.024	0.006	0.0001	-0.075	0.022	0.001

All matching covariates were included in the regressions, including district level effects. All mediator regressions also include baseline levels of agricultural activity, poverty and population density.

Table A9. Indirect mediation effects for changes in agricultural activity, poverty and population density

Intermediate mediator		Δ Pop. density			Δ Poverty		
Main Mediator		Est.	95% CI Lower	95% CI Upper	Est.	95% CI Lower	95% CI Upper
Δ Ag. activity	ACME (T)	0.003	-0.007	0.010	0.004	-0.007	0.010
	ACME (C)	0.009	-0.006	0.020	0.008	-0.006	0.020
	ACME (μ)	0.006	-0.006	0.020	0.006	-0.006	0.020
	ADE (T)	0.109	0.019	0.200	0.110	0.021	0.200
	ADE (C)	0.114	0.024	0.200	0.114	0.025	0.200
	ADE (μ)	0.112	0.021	0.200	0.112	0.023	0.200
	Total Effect	0.118	0.005	0.190	0.118	0.005	0.190
		Δ Ag. activity					
Δ Poverty	ACME (T)	0.001	-0.009	0.010			
	ACME (C)	-0.003	-0.014	0.010			
	ACME (μ)	-0.0004	-0.010	0.010			
	ADE (T)	0.120	0.032	0.210			
	ADE (C)	0.116	0.027	0.210			
	ADE (μ)	0.119	0.030	0.210			
	Total Effect	0.118	0.005	0.190			
		Δ Ag. activity					
Δ Pop. density	ACME (T)	0.007	-0.008	0.020			
	ACME (C)	0.008	-0.016	0.030			
	ACME (μ)	0.007	-0.011	0.030			
	ADE (T)	0.110	0.010	0.210			
	ADE (C)	0.111	0.018	0.200			
	ADE (μ)	0.110	0.014	0.210			
	Total Effect	0.118	0.005	0.190			

ACME = Average Causal Mediation Effect; ADE = Average Direct Effect.

Table A10. Descriptive statistics of international migrants aged > 16 years

Census year	Male ratio	Mean age of migrant	Mean time spent abroad
2001	0.895	25.938 (8.678)	4.851 (6.784)
2011	0.790	28.286 (12.719)	5.726 (14.450)

Standard deviations are presented in parentheses

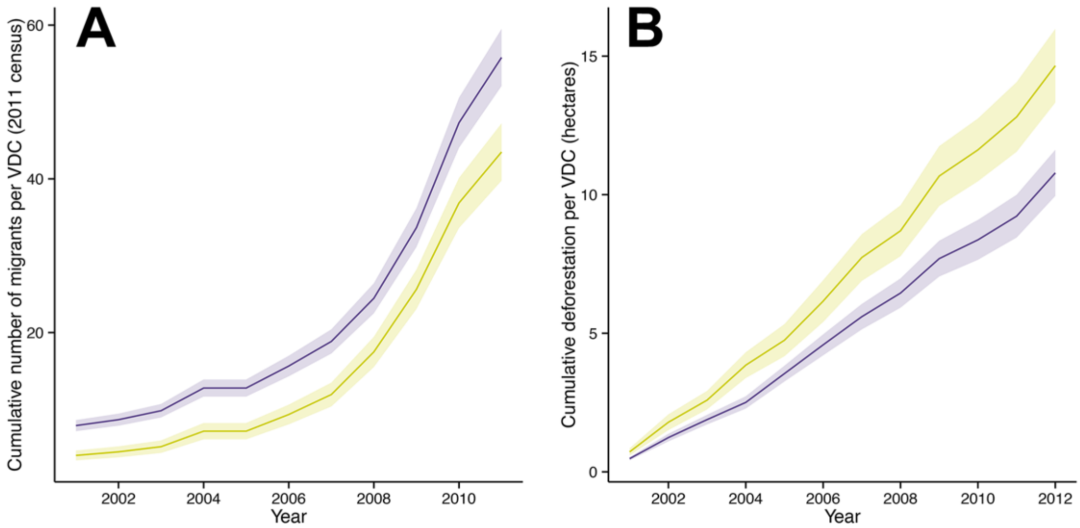

Fig. A8. Cumulative increases in international migration (*A*) and deforestation (*B*) between 2000 and 2012 for areas defined as "high" (purple) or "low" (yellow) international migration in 2001. Solid lines represent means at level of the VDC and shaded areas represent standard errors. Curves were generated using the matched dataset.

Table A11. Covariate balance before and after optimal full matching using international migration in 2012 and the MSFP dataset for all households used to model changes in irrigated and partially irrigated land

	Before Matching			After Matching		
	Means Treated *(n = 189)*	Means Control *(n = 2664)*	Stand. Mean Diff.	Means Treated *(n = 188)*	Means Control *(n = 2462)*	Stand. Mean Diff.
Propensity score	0.098	0.064	0.563	0.096	0.097	-0.011
Household size	5.577	5.119	0.153	5.590	5.523	0.022
Household assets[Yes]	0.138	0.147	-0.028	0.138	0.136	0.006
Household assets[No]	0.862	0.853	0.028	0.862	0.864	-0.006
Sanitation[Yes]	0.392	0.516	-0.254	0.394	0.297	0.198
Clean Water[Yes]	0.587	0.596	-0.017	0.585	0.600	-0.030
Electricity[Yes]	0.434	0.489	-0.111	0.436	0.474	-0.076
Quality wall material[Yes]	0.815	0.838	-0.058	0.814	0.792	0.056
Minimum schooling[Yes]	0.952	0.894	0.275	0.952	0.944	0.040
Children in school[Yes]	0.423	0.403	0.041	0.426	0.434	-0.016
National migration[Yes]	0.037	0.053	-0.084	0.037	0.043	-0.028
Baseline land for cultivation	1.357	1.195	0.067	1.364	1.470	-0.044
Baseline area dedicated to cultivation	2.770	2.340	0.100	2.539	2.798	-0.060
Baseline agricultural inputs spending	37.930	40.885	-0.046	38.131	38.133	0.000
Baseline agricultural labor spending	23.960	26.841	-0.061	24.087	20.061	0.086
Travel time to nearest road	1.580	1.990	-0.212	1.587	1.511	0.039
MSFP participation[Yes]	0.169	0.192	-0.060	0.170	0.141	0.078
Slope	20.065	21.285	-0.137	20.016	21.629	-0.182
District[§]	0.052	0.049	-0.021	0.052	0.052	-0.043

[§] Data are presented as the mean across all Districts

Table A12. Covariate balance before and after optimal full matching using international migration in 2012 and the MSFP dataset for households with irrigated or partially-irrigated land in either 2012 or 2015 used to model changes in agricultural inputs and hired labor.

	Before Matching			After Matching		
	Means Treated *(n = 135)*	Means Control *(n = 1893)*	Stand. Mean Diff.	Means Treated *(n = 135)*	Means Control *(n = 1728)*	Stand. Mean Diff.
Propensity score	0.107	0.064	0.595	0.107	0.107	0.002
Household size	5.882	5.179	0.235	5.882	5.819	0.021
Household assets[Yes]	0.141	0.148	-0.021	0.141	0.150	-0.027
Household assets[No]	0.859	0.852	0.021	0.859	0.850	0.027
Sanitation[Yes]	0.378	0.508	-0.268	0.378	0.330	0.099
Clean Water[Yes]	0.607	0.585	0.046	0.607	0.609	-0.003
Electricity[Yes]	0.459	0.502	-0.086	0.459	0.458	0.003
Quality wall material[Yes]	0.859	0.841	0.052	0.859	0.871	-0.032
Minimum schooling[Yes]	0.948	0.897	0.230	0.948	0.955	-0.029
Children in school[Yes]	0.452	0.415	0.074	0.452	0.429	0.046
National migration[Yes]	0.044	0.048	-0.015	0.044	0.055	-0.051
Baseline land for cultivation	1.430	1.341	0.039	1.430	1.435	-0.002
Baseline area dedicated to cultivation	2.520	2.414	0.044	2.520	2.464	0.023
Baseline agricultural inputs spending	34.562	39.479	-0.082	34.562	38.587	-0.067
Baseline agricultural labor spending	20.861	25.096	-0.102	20.861	18.520	0.057
Travel time to nearest road	1.761	2.105	-0.167	1.761	1.673	0.043
MSFP participation[Yes]	0.200	0.192	0.019	0.200	0.216	-0.041
Slope	20.685	21.386	-0.083	20.685	21.904	-0.145
District[§]	0.052	0.051	-0.035	0.052	0.052	-0.018

[§] Data are presented as the mean across all Districts

Table A13. Post-matched regression coefficients, standard errors and significance values for changes in the amount irrigated and partially-irrigated agricultural land, changes in the amount of agricultural in inputs, and changes in the amount of hired labor as functions of the treatment variable (international migration in 2012) and the remaining covariates.

		No interaction effect			Interaction effect		
		Coef.	S.E.	P	Coef.	S.E.	P
Δ Agr. land	Migration[High]	0.077	0.060	0.197	-0.245	0.146	0.098
	Slope	-0.006	0.004	0.167	-0.007	0.004	0.126
	Migration[High]* Slope				0.021	0.016	0.017
	[Adj. R^2]	[0.435]			[0.436]		
Δ Agr. inputs	Migration[High]	0.426	0.248	0.086	2.236	0.847	0.0082
	Slope	-0.028	-0.020	0.178	-0.024	0.021	0.250
	Migration[High]* Slope				-0.080	0.035	0.024
	[Res. Deviance]	[1609.5]			[1604.0]		
	[AIC]	[1483.7]			[1481.1]		
Δ Agr. labor	Migration[High]	0.235	0.256	0.359	0.248	0.661	0.707
	Slope	-0.020	0.021	0.333	-0.020	0.021	0.332
	Migration[High]* Slope				0.0006	0.030	0.981
	[Res. Deviance]	[1463.5]			[1463.5]		
	[AIC]	[1350]			[1352.1]		

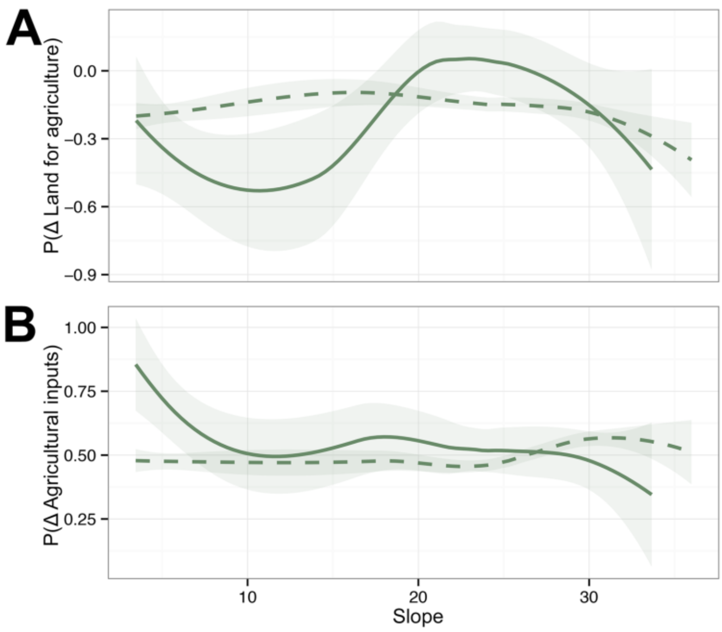

Fig. A9. Predicted probabilities of changes in irrigated and partially-irrigated land (A) and agricultural inputs (B) for households with (solid lines) and without migration (dashed lines) along increases in slope. Predicted probabilities were calculated from post-matching regressions modeling changes in irrigated and partially-irrigated agricultural land, and agricultural inputs as functions of international migration and remaining covariates. Results suggest that the effect of international migration on changes in irrigated and partially-irrigated land, and agricultural inputs is moderated by slope (impacts of international migration were greatest on lower slopes), which we use as a measure of agricultural suitability (Table S15). Lines were generated using LOESS smoothing functions and 95% confidence intervals (shaded areas).